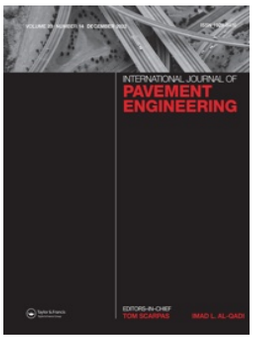

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Continuous deflection monitoring of flexible pavement under varying environmental conditions using embedded sensors

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ABSTRACT

This study investigates the influence of pavement temperature on deflection measurements obtained from embedded geophones and accelerometers installed in an instrumented flexible pavement section on the E16 motorway in Borlänge, Sweden. The analysis is based on case-wise heavy-vehicle passages recorded during a continuous monitoring period spanning Autumn 2024 to Summer 2025, encompassing a wide range of axle configurations, gross vehicle weights, travel speeds, and near-surface pavement temperatures ranging from approximately −11 °C to over 24 °C. Vibration velocity and acceleration signals were processed to estimate peak pavement surface deflections, which were subsequently normalised by load and related to pavement temperature using correlation analysis, one-way ANOVA, and regression modelling. Two empirical temperature–deflection correction models, linear and exponential, were developed to normalise deflections to a reference temperature. Both models significantly reduced temperature-induced variability in the measured deflections; however, the exponential model provided more effective overall correction, consistent with the nonlinear temperature-dependent stiffness behaviour of asphalt materials. Temperature-corrected deflections showed substantially improved agreement with multilayer elastic responses computed using the ERAPave software, with coefficients of determination reaching approximately 0.86 and normalised RMSE values reduced to less than 10% after exponential correction. The results demonstrate that embedded geophones or accelerometers, when combined with appropriate temperature normalisation, can enable accurate, year-round pavement response monitoring at traffic speed in cold and seasonally variable climates.

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Pavement deflection monitoring; temperature correction; geophones; accelerometers; cold-climate pavements; ERAPave

Introduction

Continuous assessment of pavement structural response is fundamental to mechanistic–empirical pavement design, performance evaluation, and asset management, as pavement surface deflection directly reflects the load-bearing capacity and stiffness of the layered system (Katicha et al., 2022; Kim et al., 1995; Pais et al., 2018). Consequently, deflection measurements have been widely used to assess pavement integrity, back-calculate material properties, and support maintenance and rehabilitation decision-making (Hu et al., 2022; Mun Park et al., 2002). Conventional deflection-measurement technologies, including the Falling Weight Deflectometer (FWD) and Heavy Weight Deflectometer (HWD), are widely regarded as reliable project-level assessment tools (Hamidi et al., 2025). However, their application is constrained by traffic disruption, safety considerations, high operational costs, and low temporal resolution, as measurements are typically conducted infrequently. More recent developments, such as the traffic-speed deflection device (TSDD), enable the collection of deflection data at near-traffic speeds, significantly improving network-level efficiency (Hamidi et al., 2025; Katicha et al., 2022). Nevertheless, TSDD systems remain capital-intensive and primarily suited for periodic surveys rather than continuous structural monitoring.

To address these limitations, pavement response monitoring (PRM) systems based on permanently embedded sensors have received increasing attention. Reviews of instrumented pavements document

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extensive use of strain gauges, pressure cells, thermistors, multidepth deflectometers, and fibre-optic sensors to capture pavement response under real traffic and environmental conditions (Barbieri & Lou, 2024; Barriera et al., 2020; Fahad et al., 2022; Karimi & Mallick, 2023; Khan et al., 2020). These systems provide high temporal resolution without disrupting traffic, but introduce challenges related to installation complexity, sensor durability, calibration stability, and data interpretation (Tabatabaee & Sebaaly, 1990).

Within this context, vibration-based embedded sensors such as geophones and accelerometers have been proposed as cost-effective alternatives for capturing pavement deflection under moving traffic (Bahrani et al., 2020a; Bidgoli & Erlingsson, 2026; Duong et al., 2020; Leiva-Padilla & Blanc, 2025). By measuring vertical velocity or acceleration and applying appropriate filtering and numerical integration techniques, these sensors enable estimation of pavement surface deflection without specialised survey vehicles. Controlled full-scale testing, such as accelerated pavement testing (APT), heavy vehicle simulator (HVS) experiments, and in-service field deployments, has demonstrated reasonable agreement among sensor-derived deflections, reference displacement sensors, multilayer elastic simulations, and FWD measurements (Arbabpour Bidgoli & Erlingsson, 2025; Bahrani et al., 2020b; Nasimifar et al., 2016; Zhang & Otto, 2021).

Despite these advances, most reported applications of geophones and accelerometers have been limited to short-term monitoring campaigns and conducted predominantly in mild or moderate climates (Bidgoli & Erlingsson, 2026). As a result, the influence of environmental variability, particularly pavement temperature and seasonal effects, on vibration-based deflection measurements remains insufficiently quantified. This limitation is critical in cold and seasonally variable climates, where asphalt stiffness, unbound layer behaviour, and overall pavement response vary substantially throughout the year (Bilodeau & Yi, 2019; Salour & Erlingsson, 2013). Specifically, temperature gradients within asphalt layers are known to directly influence pavement mechanical response and measured deflections (Hu et al., 2022; Kim et al., 1995; Ramos García & Castro, 2011). These gradients also affect the dynamic characteristics of vibration signals recorded by embedded sensors, including frequency content and amplitude attenuation (Leiva-Padilla & Blanc, 2025; Nasimifar et al., 2016). While robust temperature correction procedures are now well established for FWD and increasingly for TSDD measurements (Březina et al., 2022; Mun Park et al., 2002; Nasimifar et al., 2018; National Academies of Sciences & E. & Medicine, 2024; Shen et al., 2025; Zhang & Fu, 2023), equivalent correction frameworks for embedded vibration-based sensors remain largely undeveloped.

This study addresses this gap by evaluating pavement deflection measurements obtained from co-located geophones and accelerometers installed on the E16 motorway in Borlänge, Sweden. The site experiences pronounced seasonal temperature variation, making it well-suited for investigating temperature-induced variability in sensor-based deflection estimates. By integrating mechanical response data with environmental measurements and analysing multiple heavy-vehicle loading cases, the study examines how temperature and seasonal effects influence signal characteristics, displacement estimation, and derived deflection measures. The results support the development of continuous, year-round pavement deflection monitoring systems based on low-cost embedded geophones and accelerometers. This work builds on and continues the study by Bidgoli and Erlingsson (2026).

Research background

Deflection-based pavement evaluation and temperature effects

Deflection-based pavement evaluation has been a cornerstone of pavement engineering for decades, with FWD testing widely used to support mechanistic–empirical design and rehabilitation decision-making (Kim et al., 1995; Pais et al., 2018). Measured deflections are highly sensitive to asphalt temperature due to the complex behaviour of asphalt concrete, resulting in significant daily and seasonal variability in deflection basins and backcalculated stiffness (Hu et al., 2022; Mun Park et al., 2002). Numerous studies have shown that neglecting temperature effects can bias the interpretation of pavement stiffness and bearing capacity, potentially leading to incorrect maintenance or rehabilitation decisions (Kim et al., 1995; Ramos García & Castro, 2011).

Early temperature correction approaches often relied on mean pavement or surface temperature; however, subsequent research demonstrated that such simplifications cannot adequately represent thermal gradients through the asphalt layer or the hysteresis between heating and cooling cycles (Kim et al., 1995;

Zheng et al., 2017). To address these limitations, more advanced approaches introduced the concept of an effective pavement temperature—commonly linked to a representative depth (e.g. mid-depth or a specified layer depth), which improves normalisation of deflections and the consistency of backcalculated moduli across varying test conditions (Hu et al., 2022; Mun Park et al., 2002; Orosa & Li, 2025). Long-term and instrumented monitoring studies further indicate that temperature-corrected deflections help distinguish environmental influences from true structural deterioration, especially in climates affected by seasonal freezing and thawing (Bilodeau & Yi, 2019; Březina et al., 2022; Diaz Flores et al., 2024). Consequently, recent guidance emphasises systematic adjustment of FWD measurements for temperature (and, where relevant, moisture) to ensure meaningful comparisons over time and across sites (National Academies of Sciences & E. & Medicine, 2024).

Traffic speed deflectometer and environmental normalisation

The TSDD represents a major advancement in deflection measurement by enabling data collection at traffic speed, significantly improving operational safety, minimising traffic disruption, and substantially increasing productivity for network-level structural assessment (Hamidi et al., 2025; Katicha et al., 2022). Extensive research has focused on TSDD data processing, repeatability, correlation with FWD, and integration into pavement management systems (Hamidi et al., 2025; Katicha et al., 2022). A consistent outcome across these investigations is that asphalt temperature is the dominant factor affecting measured deflections, often exerting a greater influence than vehicle speed within typical operating ranges (Jia et al., 2021; Nasimifar & Shojaee, 2021; Nasimifar et al., 2018; Zhang & Fu, 2023). As a result, numerous temperature correction models have been proposed for TSDD measurements, ranging from regression-based approaches to advanced machine-learning techniques such as artificial neural networks (Shen et al., 2025). These studies generally conclude that temperature normalisation is not an auxiliary post-processing step but a prerequisite for long-term structural trend analysis and for defensible comparisons across sites, seasons, and survey campaigns using TSDD measurements.

Pavement response monitoring with embedded sensors

PRM using embedded instrumentation offers a complementary perspective to episodic deflection surveys, enabling continuous observation of structural response under actual traffic loading and evolving environmental conditions. Reviews of in-situ monitoring practice document rapid growth in the use of strain gauges, pressure cells, deflection-related sensors, and thermal and climatic instrumentation, motivated by the need for time-resolved condition information to support performance assessment and asset management (Barriera et al., 2020; Fahad et al., 2022; Karimi & Mallick, 2023; Tabatabaee & Sebaaly, 1990).

Instrumented test sections and full-scale experiments have demonstrated the value of PRM for quantifying fatigue accumulation, rutting-related response, and seasonal stiffness evolution, particularly when measurements are interpreted in conjunction with mechanistic models and independent structural tests (Barriera et al., 2021; Donev et al., 2023; Khan et al., 2020; Saliko & Erlingsson, 2023). A recurring conclusion is that environmental variability, most notably temperature and, where relevant, moisture, often dominates response fluctuations; without explicit environmental conditioning, apparent changes in measured response can be incorrectly attributed to structural deterioration (Barbieri & Lou, 2024). Consequently, integrated monitoring strategies that pair mechanical response sensing with co-located environmental measurements are increasingly emphasised as the basis for robust inference of structural change from long-term PRM datasets (Fahad et al., 2022; Karimi & Mallick, 2023).

Accelerated pavement testing and heavy vehicle simulator as controlled validation platforms

APT and HVS facilities have played an important role in the development of PRM by providing controlled, repeatable loading conditions under which embedded instrumentation can be evaluated over compressed time scales (Bilodeau & Doré, 2020; Du Plessis et al., 2018; Fladvad & Erlingsson, 2021; Neves et al., 2023; Saevarsdottir et al., 2014). Across international APT and HVS programmes, instrumented test sections have incorporated a wide range of embedded sensors to monitor pavement response, damage accumulation,

and structural change, including strain gauges, pressure cells, thermocouples, displacement sensors, and, increasingly, vibration-sensitive devices (Bilodeau & Doré, 2020; Duong et al., 2020; Liu et al., 2024; Neves et al., 2023; Saevarsdottir et al., 2014). Such facilities have been used to assess long-term pavement response over a reduced timescale and to examine how embedded sensing systems respond under controlled, repeated wheel loading, thereby bridging the gap between controlled experiments and in-service field monitoring.

Reviews of APT instrumentation further show that embedded sensing has become a central component of structural assessment in full-scale pavement experiments, particularly for tracking stress–strain states, deformation development, and other deflection-related responses under repeated loading (Liu et al., 2024; Neves et al., 2023; Saevarsdottir et al., 2014). More recent sensor-based studies also demonstrate that controlled APT environments enable clearer interpretation of spatial and temporal pavement-response patterns than is often possible under open-traffic conditions (Liu et al., 2024). In this respect, APT and HVS research provide an important methodological bridge to vibration-based monitoring, offering a controlled platform for evaluating geophones, accelerometers, and related response-measurement approaches before their transfer to continuous monitoring under real traffic and environmental variability (Bahrani et al., 2020a; Duong et al., 2020). This connection is especially relevant to the present study, which extends that line of work from controlled loading environments to year-round, in-service pavement deflection monitoring using embedded vibration sensors (Bidgoli & Erlingsson, 2026).

Vibration-based embedded sensors for deflection monitoring

Vibration-based embedded sensing, typically using geophones and accelerometers, has been proposed as a cost-effective approach for estimating pavement deflection under moving traffic, with the potential to scale PRM from localised experiments toward broader continuous monitoring applications (Bahrani et al., 2020a; Bidgoli & Erlingsson, 2026; Duong et al., 2020). Conceptually, these sensors measure velocity or acceleration, which can be processed through filtering and integration to recover displacement time histories representative of traffic-induced deflection.

Controlled APT experiments have demonstrated that careful signal treatment is crucial for obtaining stable deflection estimates, and that processed sensor-derived deflections can align well with reference displacement sensors under controlled loading conditions (Bahrani et al., 2020a; Leiva-Padilla & Blanc, 2025). Field deployments further support the feasibility of long-duration operation and remote acquisition, demonstrating that embedded geophones can capture traffic signatures and deflection-related indicators over extended periods in service conditions (Bahrani et al., 2023; Duong et al., 2020). Recent work has also reported close agreement between processed measurements and mechanistic predictions of in-service pavements, strengthening the case for using vibration-based sensing as a practical proxy for continuous deflection monitoring (Arbabpour Bidgoli & Erlingsson, 2025; Bidgoli & Erlingsson, 2026). Despite these advances, most applications have been limited in duration and climatic scope, and few studies examine how seasonal temperature changes affect the long-term reliability of reconstructed displacements. Filling this gap is necessary to move from short- and medium-term demonstrations to robust, temperature-aware monitoring systems for multi-year performance monitoring.

A concise overview of the literature on deflection measurement, temperature effects, and sensing technologies is provided in Table 1. The table organises major research threads, summarises dominant methodologies, and highlights their contributions that motivate the present focus on long-term, temperature-aware evaluation of vibration-based embedded deflection monitoring systems.

Evidence-based research gap

As summarised in Table 1, temperature effects on deflection measurements are well established, and mature correction frameworks exist for conventional deflection devices. For FWD, representative temperature concepts and regression-based adjustments have been extensively developed and applied to improve the comparability of deflections and backcalculated stiffness (Březina et al., 2022; Hu et al., 2022; Kim et al., 1995; Le et al., 2022; Mun Park et al., 2002; Orosa and Li, 2025; Pais et al., 2018). For TSDD and related devices, studies consistently indicate that asphalt temperature dominates operational influences within typical survey ranges

Table 1. Summary of literature on pavement deflection measurements and temperature effects.

Reference(s)	Research thread	Data/Method	Main contribution
Ramos García and Castro (2011); Zheng et al. (2017)	Temperature–deflection relationship	Field data + statistical modelling	Quantified temperature effects on deflection magnitude and basin characteristics.
Březina et al. (2022); Diaz Flores et al. (2024); Hu et al. (2022); Kim et al. (1995); Le et al. (2022); Mun Park et al. (2002); Orosa and Li, 2025; Pais et al. (2018)	FWD temperature correction	Seasonal FWD + regression correction	Developed practical temperature-correction frameworks using representative/effective temperature concepts to normalise deflections and improve backcalculated stiffness consistency.
Bilodeau and Yi, 2019; Diaz Flores et al. (2024); Salour and Erlingsson (2013)	Seasonal and cold-climate effects	Seasonal field data + frost/thaw modelling	Documented freeze–thaw and seasonal variability affecting pavement response and structural interpretation.
Hamidi et al. (2025); Jia et al. (2021); Katicha et al. (2022); Liao et al. (2019); Nasimifar and Shojaee (2021); Nasimifar et al. (2018); Shen et al. (2025); Zhang and Fu, 2023	TSD environmental normalisation	Traffic-speed data + regression and ML correction	Established traffic-speed deflection measurement for network assessment and proposed environmental normalisation models, emphasising temperature sensitivity.
Barriera et al. (2021); Donev et al. (2023); Khan et al. (2020); Ma et al. (2022); Saliko and Erlingsson (2023)	PRM with embedded sensors	Instrumented field sections + controlled loading; mechanistic backcalculation	Revealed continuous, sensor-based quantification of pavement response and temperature-dependent stiffness, enabling time-resolved interpretation of structural behaviour.
Bahrani et al. (2020a); Bahrani et al. (2020b); Duong et al. (2020); Nasimifar et al. (2016); Zhang and Otto, 2021	Vibration-based deflection estimation	Lab/APT/HVS/field data + filtering; integration; numerical transform	Demonstrated the feasibility of reconstructing deflection from geophones/accelerometers and established key signal-processing steps.
Arbabpour Bidgoli and Erlingsson (2025); Bahrani et al. (2023); Bidgoli and Erlingsson (2026); Leiva-Padilla and Blanc, 2025	Embedded sensor-based deflection measurement	Long-term field validation + signal processing; comparison	Conducted field-validated embedded vibration systems and automated processing approaches consistent with mechanistic expectations and/or reference measurements.
National Academies of Sciences and E. & Medicine (2024); Pierce et al. (2024)	Guidance and standardisation	LTPP/SMP data analyses + practices and guidance	Provided recommended practices for environmental correction (temperature/moisture) to support comparability of structural responses.

and have proposed regression- and ML-based normalisation approaches (Jia et al., 2021; Katicha et al., 2022; Liao et al., 2019; Nasimifar & Shojaee, 2021; Nasimifar et al., 2018; Shen et al., 2025; Zhang and Fu, 2023). These developments are increasingly reflected in guidance that emphasises systematic environmental correction to support temporal and spatial comparability (National Academies of Sciences & E. & Medicine, 2024; Pierce et al., 2024).

In contrast, embedded vibration-based deflection monitoring (geophones/accelerometers) still lacks an equivalent, field-validated temperature-normalisation framework suitable for multi-season and cold-climate operation. Although prior work shows that vibration signals can be processed to recover traffic-induced deflections and that the resulting estimates can agree with reference measurements or mechanistic expectations (Bahrani et al., 2023; Bidgoli & Erlingsson, 2026; Duong et al., 2020; Leiva-Padilla & Blanc, 2025; Nasimifar et al., 2016; Zhang & Otto, 2021), most studies provide limited evidence on how seasonal temperature variability affects the long-term stability and comparability of the derived deflection measures. This limitation is particularly consequential in cold and seasonally variable regions, where freeze–thaw processes and large stiffness swings can dominate structural response and confound interpretation (Bilodeau & Yi, 2019; Saliko & Erlingsson, 2023; Salour & Erlingsson, 2013).

Accordingly, the central gap is the lack of long-term, cold-climate field studies that combine co-located vibration and temperature sensing to quantify sensor-specific temperature–deflection relationships under real heavy-vehicle loading and to develop and validate practical correction models for vibration-derived pavement surface deflections. A related gap is the limited number of direct comparisons between geophones and accelerometers under the same traffic and environmental conditions, which is necessary to establish relative reliability and operational constraints and to support implementation of low-cost embedded vibration sensors for continuous, year-round pavement deflection monitoring.

Methodology

Instrumentation and data collection

Field measurements were conducted on the E16 Motorway in Borlänge, Sweden, using an integrated in-situ sensor system embedded within the right wheel path of the pavement surface. The sensor setup described here represents one part of the broader instrumentation installed at the project site, and consists of geophones, accelerometers, and thermistors placed at different depths to continuously capture pavement response and environmental conditions. Figure 1 shows the sensor setups installed at the measurement site, and the season-specific elastic moduli presented in Table 2 were adopted from FWD backcalculation previously reported for the same pavement section by Salour and Erlingsson (2013). These properties were obtained independently of the embedded-sensor measurements analysed in the present study and were used to represent the corresponding seasonal stiffness conditions of the asphalt layer, unbound layers, and subgrade.

In this measurement site, two sets of five GS-One LF geophones were embedded at a depth of 7.0 cm, while two sets of three Silicon Designs 2210-002 accelerometers were installed at a shallower depth of 2.5 cm. The sensors were arranged with lateral offsets of 15 cm to capture the maximum wheel-path response and were secured using a milling-and-embedding procedure with Densolastic SV adhesive. Geophones recorded vibration velocity and accelerometers recorded acceleration; both were sampled at 1000 Hz to ensure high temporal resolution during heavy-vehicle loading. In addition to the dynamic sensors, thermocouples were installed at depths of 4, 8, and 14 cm within the asphalt layer to monitor near-surface pavement temperature, complemented by an air-temperature probe positioned near the site. In this study, the pavement temperature (T) used in all analyses is defined as the arithmetic mean of these three thermocouple readings (°C).

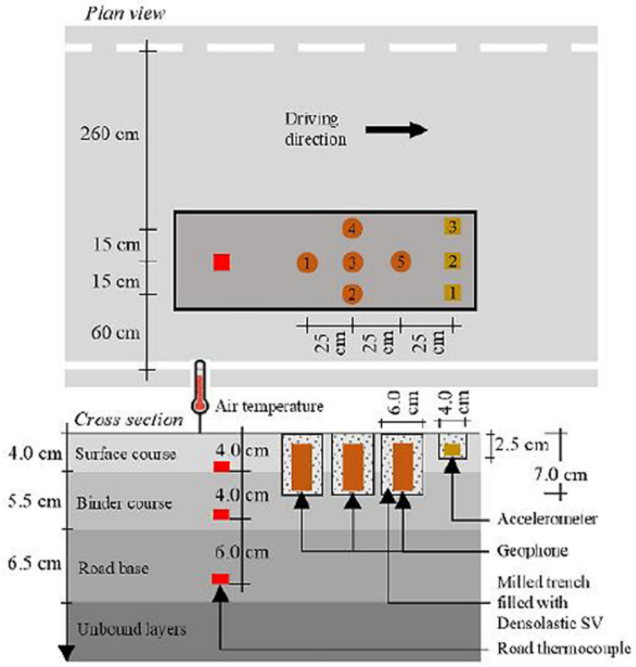

Figure 1. Sensor setup installed on the E16 motorway in Borlänge, Sweden.

Table 2. Pavement layer properties.

Layers	Materials	Thickness (cm)	E-Modulus (MPa) in November	E-Modulus (MPa) in February*	E-Modulus (MPa) in May	E-Modulus (MPa) in August	Poisson's ratio (-)
1	Surface course	4.0	9000	20000	2500	5000	0.35
2	Binder course	5.5	9000	20000	2500	5000	0.35
3	Road base	6.5	9000	20000	2500	5000	0.35
4	Unbound base	8.0	400	2600	350	350	0.35
5	Subbase	42.0	300	2200	270	250	0.35
6	Protection layer	45.0	250	1200	250	200	0.35
7	Subgrade	NA	120	600	120	100	0.35

* Note: the frost depth was 122.5 cm.

Four datasets were randomly collected across different seasons. The first dataset comprised eight heavy-vehicle passages recorded in November (week 46), 2024, under cold autumn conditions with air temperatures ranging from 2.1 °C to 5.5 °C. The second dataset included eight heavy-vehicle passages recorded in February (week 7), 2025, under winter conditions with air temperatures ranging from −19.1 °C to −4.9 °C. The third dataset included eight additional heavy-vehicle passages recorded in May (week 21), 2025, under spring conditions with air temperatures ranging from 9.8 °C to 22.5 °C. The fourth dataset included eight heavy-vehicle passages recorded in August (week 35), 2025, under summer conditions with air temperatures ranging from 6.7 °C to 9.5 °C. Together, these datasets provided a broad range of pavement temperatures for assessing temperature sensitivity across four seasons. The selected cases represent a range of axle configurations, gross vehicle weights (GVW), and speeds while sharing the consistent pavement structure. Table 3 summarises the characteristics of the selected heavy-vehicle cases, and Table 4 presents four sample six-axle loading configurations. Vehicle attributes and axle configurations were obtained from a weigh-in-motion (WIM) system located approximately 25 m upstream of the embedded sensor installation in the same traffic lane. WIM and sensor records were matched using vehicle passage times corrected for the 25 m offset and the recorded vehicle speed, while ambiguous matches were excluded to minimise possible mismatches. Because the sensor arrays were positioned in the right wheel path, the corresponding right-side half-axle loads were used in subsequent analyses. The effects of lateral wheel position were accounted for using an averaging procedure in the load-normalisation analysis.

Data analysis

The raw velocity and acceleration signals collected from the embedded sensors were transformed into pavement deflection measurements through a structured signal-processing workflow, following the methods described by Bahrani et al. (2020a) and Bidgoli and Erlingsson (2026). The process begins with the acquisition of continuous sensor recordings during each vehicle passage. These signals are then preprocessed using a 13–50 Hz bandpass filter to remove low-frequency drift and high-frequency noise while preserving the dominant frequency content associated with pavement temperature. After filtering, the signals were transformed to the frequency domain using a Fast Fourier Transform (FFT). For each vehicle passage, the complete signal segment corresponding to the vehicle response was processed without additional windowing, followed by application of the sensor-specific transfer functions to account for the mechanical and electrical characteristics of the sensors. The corrected signal was then reconstructed in the time domain for subsequent displacement estimation. The filtered and corrected signals are amplified according to sensor sensitivity and vehicle speed, with amplification factors held constant and not adjusted for temperature. For geophones, the recorded velocity is integrated once to obtain displacement, whereas accelerometer signals are integrated twice to derive displacement. The final deflection time history is obtained by applying the Hilbert Transform to extract the deflection envelope corresponding to the axle configuration of each vehicle, where "deflection" refers to the vertical pavement displacement at the sensor location near the pavement surface.

Table 3. Characteristics* of the selected heavy-vehicle cases, including operational and seasonal information.

Case time	Axle count	GVW (kN)	Speed (km/h)	Air temp. (°C)	Mean temp. (°C) in AC	Mean moisture (%) in subbase	Mean moisture (%) in subgrade	Timestamp (M/D)
November 2024	2 - 9	210.8–668.2	76.5–88.6	2.1–5.5	0.9–3.2	1.1–1.5	22.6–22.8	11/09–11/15
February 2025	2 - 9	235.6–1252.7	67.9–87.4	−19.1–−4.9	−10.8–−5.3	1.0–1.2	21.3–21.7	02/09–02/15
May 2025	2 - 9	36.5–1123.1	84.0–93.2	9.8–22.5	14.6–24.3	1.9–2.1	23.7–23.8	05/18–05/24
August 2025	2 - 9	238.1–1311.2	80.7–92.3	6.7–9.5	9.4–14.1	2.1–2.2	25.2–25.5	08/23–08/29

*Note: all cells have a range of values from minimum to maximum.

Table 4. Sample axle loading configurations for selected vehicle cases.

						Right-side half-axle load (kN)					
Case no.	Case time	Axle count	Axle configuration*	GVW (kN)	Speed (km/h)	Axle 1	Axle 2	Axle 3	Axle 4	Axle 5	Axle 6
Case 1	November 2024	6	1S.1D+2SS+2SS	534.2	85.7	43.25	82.18	30.79	29.91	37.76	38.54
Case 2	February 2025	6	1S.1D+2SS+2SS	707.4	86.8	47.27	90.42	51.19	56.29	53.05	57.66
Case 3	May 2025	6	1S.1D+2SS+2SS	516.8	85.2	61.29	115.3	31.09	32.26	33.34	35.89
Case 4	August 2025	6	1S.2DS+2SS+1S	685.8	85.9	66.29	106.5	62.76	44.33	43.44	50.50

* Note: 1 and 2 represent single and tandem axles, while S and D represent single- and dual-wheel tires, respectively.

Figures 2–5 present examples of the processed sensor outputs for four representative cases: Case 1 in November 2024, Case 2 in February 2025, Case 3 in May 2025, and Case 4 in August 2025. All cases involved six-axle vehicles travelling at similar speeds near 86 km/h; however, the individual axle loads and gross vehicle weights varied among the cases, as summarised in Table 4. Therefore, these figures are intended to illustrate the signal-processing procedure and seasonal response characteristics rather than provide a direct equal-load comparison. Each figure shows the averaged raw signals from the geophones and accelerometers together with the final deflection envelopes obtained through the processing workflow, illustrating how pavement deflection is extracted from the recorded vibration and acceleration data.

After obtaining the deflection measurements through the signal-processing chain, the next step was to evaluate how pavement surface temperatures influence these measurements. Correlation analysis (Pearson and Spearman) was performed to quantify the relation between normalised deflection and pavement temperature, followed by a one-way ANOVA applied to temperature bins (< 0 °C, 0–10 °C, 10–20 °C, > 20 °C) to test the null hypothesis of no significant differences in deflection across thermal regimes. These intervals were selected as 10 °C thermal ranges spanning the observed pavement-temperature conditions, with subzero temperatures treated separately. The grouped ANOVA was complementary to the correlation and regression analyses, in which temperature was treated as a continuous variable.

For each case, a load-normalised surface deflection (d_{norm}) was computed by dividing the peak surface deflection by the corresponding right-side half-axle load (mm/kN). To model the temperature dependence, both linear regression and nonlinear exponential models were employed. The linear formulation,

$$d_{norm} = \beta_0 + \beta_1 T, \tag{1}$$

provides a straightforward statistical representation, whereas the exponential formulation,

$$d_{norm} = \beta_0 \cdot \exp(\beta_1 T), \tag{2}$$

was included because the asphalt layer exhibits fundamentally nonlinear temperature-dependent behaviour and, therefore, a nonlinear formulation may better capture the physical response of the material.

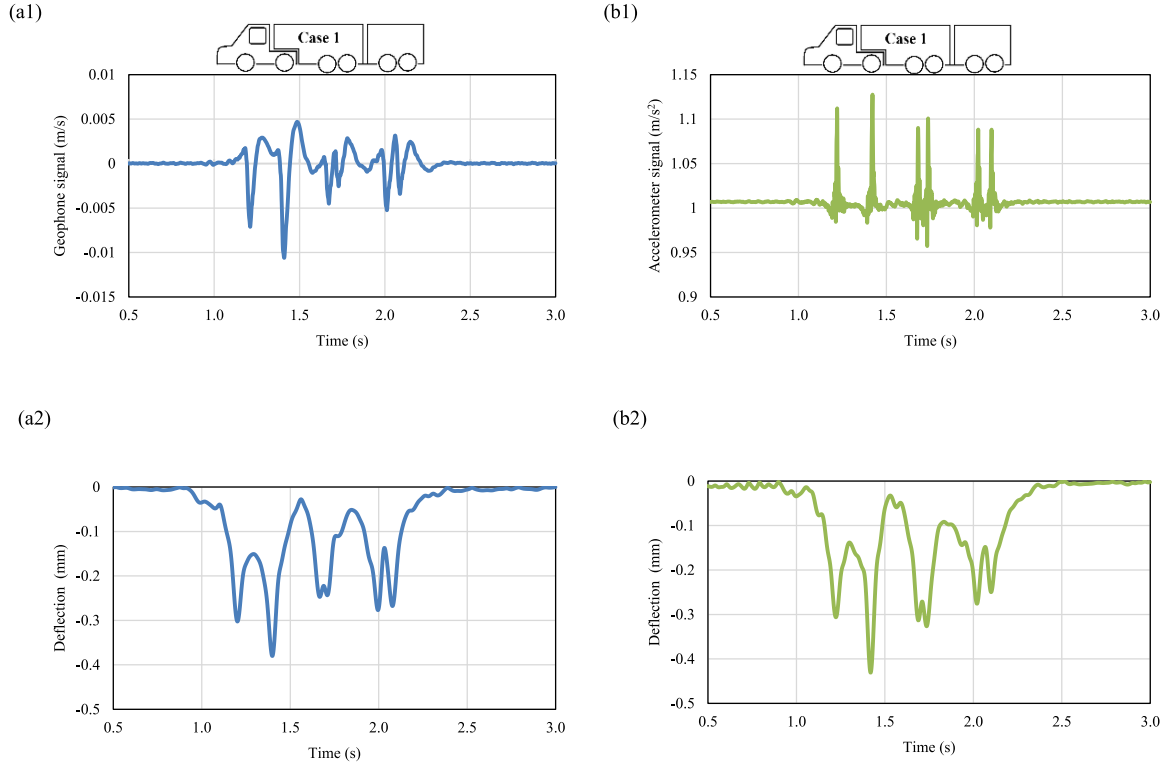

Figure 2. Deflection measurements for Case 1 in November 2024: (a1) raw geophone signals, (a2) geophone-based displacements, (b1) raw accelerometer signals, and (b2) accelerometer-based displacements.

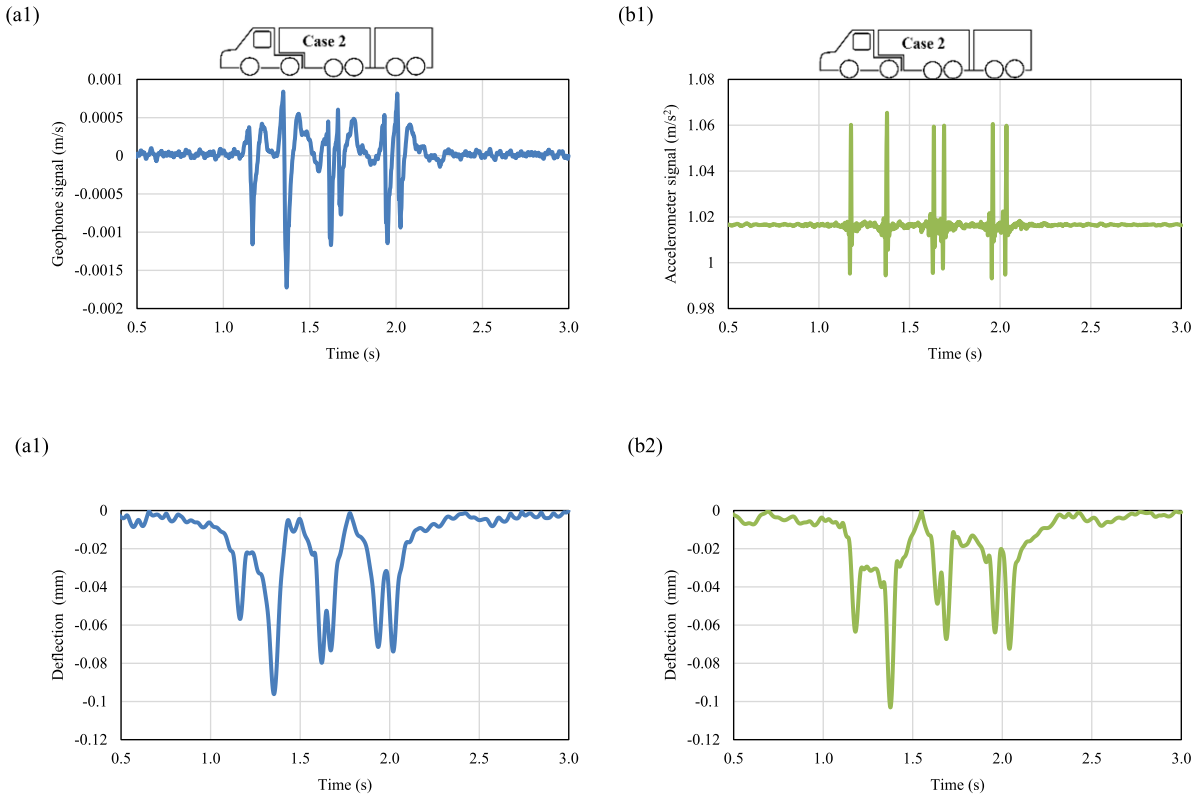

Figure 3. Deflection measurements for Case 2 in February 2025: (a1) raw geophone signals, (a2) geophone-based displacements, (b1) raw accelerometer signals, and (b2) accelerometer-based displacements.

To enable consistent comparison across cases collected at different temperatures, a data-driven reference temperature was defined. The annual mean near-surface pavement temperature at the project site, approximately + 8 °C based on thermistor measurements at depths of 4, 8, and 14 cm over a full year (Autumn 2024 to Summer 2025), was close to the reference temperature selected for this study, +10 °C ($T_{ref} = \overline{T}$). For each vehicle passage, the measured load-normalised deflection was adjusted to this reference temperature using the model parameters from Equations (1) and (2), thereby removing the model-predicted temperature effect and yielding temperature-normalised deflection values. The linear temperature-correction expression is

$$d_{corr} = d_{norm} - \beta_1(T - T_{ref}), \tag{3}$$

while the exponential correction is given by

$$d_{corr} = d_{norm} \,.\exp(-\beta_1 (T - T_{ref})), \tag{4}$$

where, d_{norm} is the peak load-normalised surface deflection (mm/kN), d_{corr} is the temperature-corrected load-normalised surface deflection (mm/kN), T is the case-specific mean near-surface pavement temperature averaged over depths of 4, 8, and 14 cm (°C), T_{ref} is the reference temperature (°C) and β_0 and β_1 are the regression model parameters.

To evaluate the temperature-correction models, the corrected deflections were compared with responses calculated using the Multilayer Elastic Response Analysis of Pavements (ERAPave) software (Erlingsson & Ahmed, 2013). ERAPave is based on multilayer elastic theory, in which the pavement layers are represented using elastic material properties. Accordingly, the asphalt concrete layer was not explicitly modelled as a linear viscoelastic material, and the ERAPave calculations are used here as a simplified mechanistic reference rather than as a complete representation of the time-dependent asphalt response. The complete axle configuration of each selected heavy vehicle was represented using axle configuration and loading information obtained from the upstream WIM station. Because the embedded sensors were located in the right wheel path, the corresponding right-side half-axle loads were used in the calculations. The unbound layers and subgrade were modelled as homogeneous, isotropic, linear-elastic materials using season-specific elastic moduli and

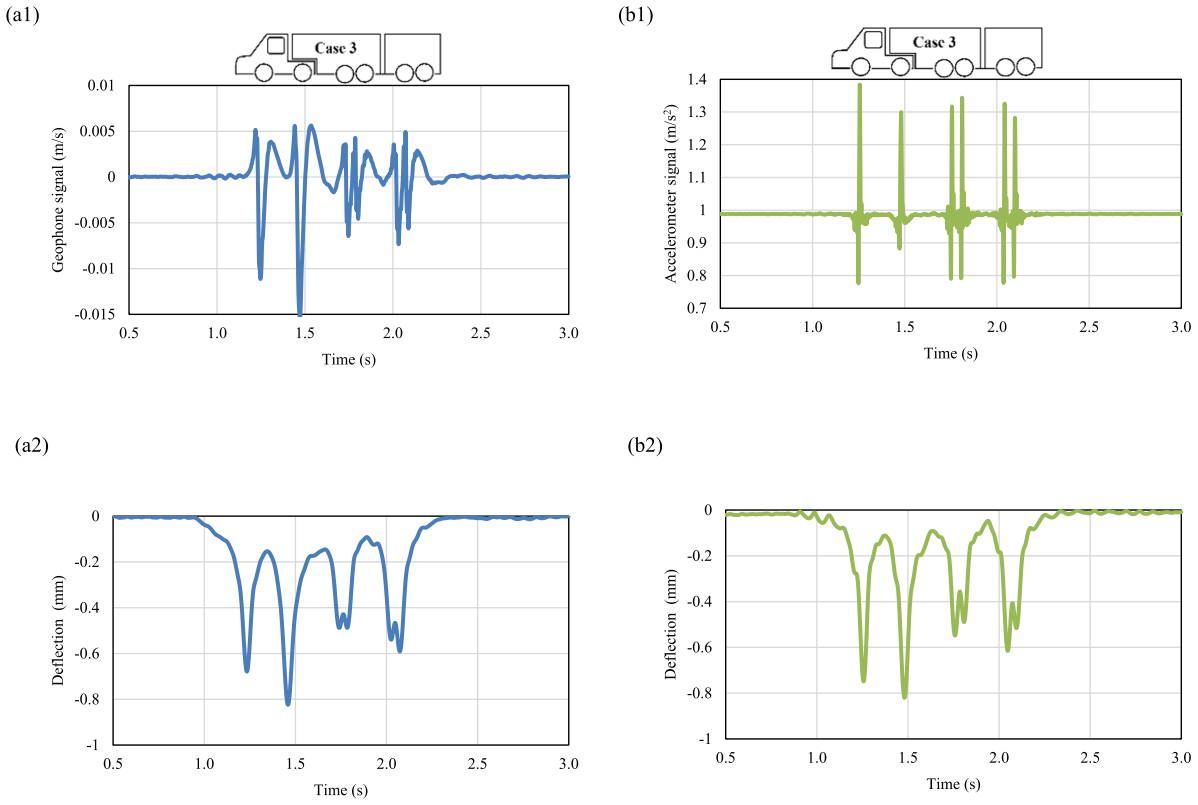

Figure 4. Deflection measurements for Case 3 in May 2025: (a1) raw geophone signals, (a2) geophone-based displacements, (b1) raw accelerometer signals, and (b2) accelerometer-based displacements.

Poisson's ratios; stress-dependent nonlinear behaviour of the granular materials was not explicitly considered. The elastic moduli were adopted independently from the FWD backcalculation reported by Salour and Erlingsson (2013), as summarised in Table 2. Figure 6 illustrates the comparison between the ERAPave-calculated and sensor-based responses for Cases 1–4.

The analysed heavy vehicles travelled within a relatively narrow traffic-speed range, with an average speed of approximately 85 km/h, resulting in broadly comparable loading durations among the selected cases. Because loading frequency is not an explicit ERAPave input and the asphalt layer is represented as linear elastic rather than viscoelastic, loading-rate effects were not modelled directly. The similar traffic speeds among the analysed cases were therefore assumed to limit differences in loading duration, although viscoelastic and frequency-dependent effects may still influence the measured pavement response. These effects are recognised as limitations of the present elastic mechanistic comparison.

Based on this reference framework, accuracy was quantified using the mean absolute error (MAE), the normalised root mean square error (NRMSE), and the coefficient of determination (R^2), based on comparisons between the peak values of the temperature-corrected deflections and the ERAPave calculations. These metrics were used to assess the reliability of the signal-processing chain and the suitability of embedded sensors for temperature-corrected continuous pavement deflection monitoring. Note that all comparisons with ERAPave are based on deflections corresponding to the near-surface sensor location, ensuring consistency between the sensor-derived response and the mechanistic reference.

Results

Temperature effects on deflection

Statistical analyses were conducted to quantify how seasonal temperature variations affect pavement surface deflections measured by the embedded accelerometers and geophones. A combined summary of correlation and ANOVA results is presented in Table 5. Both sensors revealed strong and statistically significant

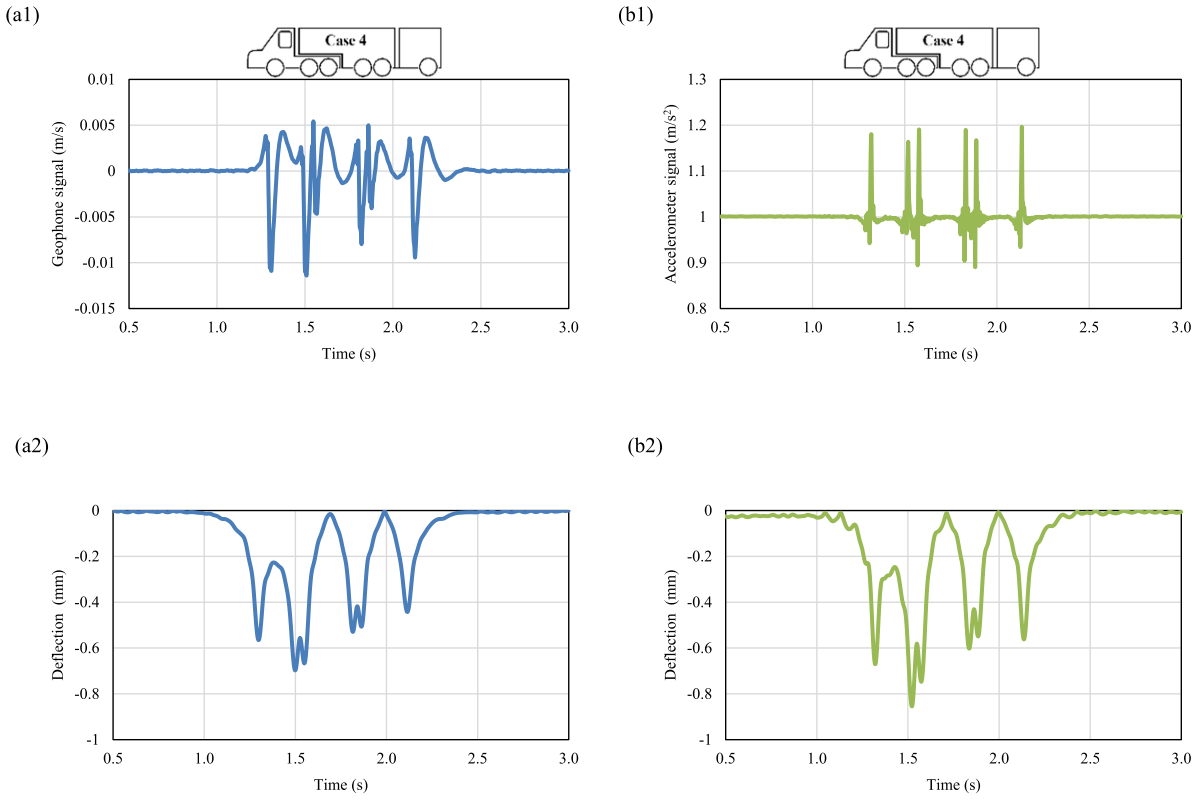

Figure 5. Deflection measurements for Case 4 in August 2025: (a1) raw geophone signals, (a2) geophone-based displacements, (b1) raw accelerometer signals, and (b2) accelerometer-based displacements.

relationships between normalised deflection and pavement temperature. Pearson correlations indicated strong negative associations between mean near-surface pavement temperature and normalised deflection for both accelerometers and geophones (accelerometers: $r = -0.89$; geophones: $r = -0.89$; $p < 0.001$). Spearman's rho confirmed similarly strong monotonic relationships (accelerometers: $\rho = -0.91$; geophones: $\rho = -0.88$; $p < 0.001$). Note that deflections are reported with a sign convention in which downward displacement is negative. Therefore, as temperature increases, peak deflections become more negative (i.e. their magnitude increases), which produces a negative correlation with temperature when signed values are used. These results indicate that warmer pavement consistently produces higher normalised deflections, reflecting reduced stiffness at elevated temperatures.

To further evaluate temperature effects, normalised deflections were compared across four temperature bins (< 0 °C, 0–10 °C, 10–20 °C, > 20 °C). One-way ANOVA revealed statistically significant differences among temperature groups for both accelerometers, $F(3,172) = 239.83$, $p < 0.001$, $\eta^2 = 0.81$, and geophones, $F(3,172) = 238.02$, $p < 0.001$, $\eta^2 = 0.81$. Mean normalised deflections became progressively more negative from the coolest to the warmest temperature bin for both sensor types, and seasonal comparisons (e.g. autumn vs. winter vs. spring vs. summer) showed the same general trend, with warmer periods producing noticeably larger normalised deflections.

Overall, these results demonstrate that pavement temperature is a dominant factor influencing embedded-sensor deflection measurements, with large and systematic changes in deflection magnitude across temperature ranges. The consistency of the correlation and ANOVA results across both sensor types strongly supports the integration of temperature-correction models into continuous pavement deflection monitoring.

Temperature–deflection modelling

To quantify the influence of pavement temperature on the measured deflections, normalised geophone-based and accelerometer-based deflection values were analysed together with the corresponding pavement surface temperatures. Two regression approaches were evaluated: a linear formulation and a nonlinear exponential

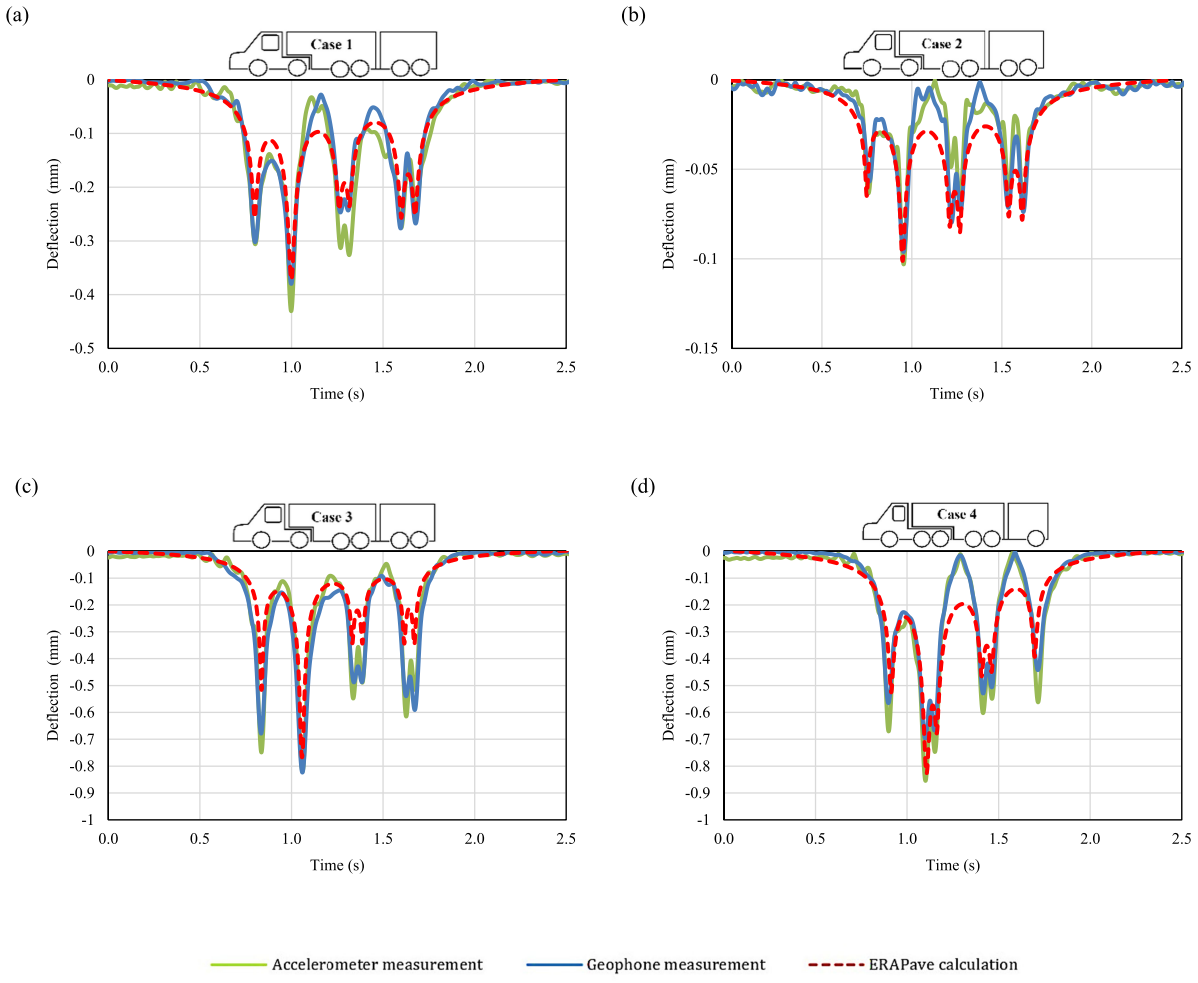

Figure 6. Deflection comparison between sensor-based measurements and ERAPave calculation for (a) Case 1 in November 2024, (b) Case 2 in February 2025, (c) Case 3 in May 2025, and (d) Case 4 in August 2025 (agreement is based on deflections corresponding to the near-surface sensor location).

Table 5. Summary of correlation and ANOVA results for temperature effects on normalised deflection.

		Mean near-surface pavement temperature					
		Pearson(r)	Spearman(ρ)	ANOVA (F-value)	Sign. (P-value)	Effect size(η^2)	(N)
Normalised deflection	Geophones	−0.89	−0.88	238.02	<0.001	0.81	176
	Accelerometers	−0.89	−0.91	239.83	<0.001	0.81	176

formulation. The objective was to determine how much of the between-case variability in deflection amplitude was attributable to temperature and to derive correction functions capable of removing this environmental bias. Before modelling, all temperature and deflection values were screened for validity; because raw deflections are negative, linear models were fitted to signed values, while exponential models used absolute magnitudes.

The resulting model parameters (β_0 and β_1), coefficients of determination (R^2), and 95% confidence intervals (CI) are presented in Table 6. Both the linear and exponential formulations produced well-behaved fits across all cases, with R^2 values ranging from 0.74 to 0.80, indicating that temperature effects can be reliably captured using simple empirical models. Across both sensor types, the negative linear coefficients (β_1) and positive exponential coefficients confirm that normalised deflections increase systematically with temperature, consistent with the observed thermal sensitivity of the pavement structure. The 95% confidence intervals for β_1 are relatively narrow and do not include zero, demonstrating a statistically significant and robust temperature effect. After applying the temperature-correction functions, residual slopes of deflection versus

Table 6. Results of temperature-corrected deflection models for geophone and accelerometer measurements.

	Geophones			Accelerometers		
	β_0 [95% CI]	β_1 [95% CI]	R^2	β_0 [95% CI]	β_1 [95% CI]	R^2
Linear regression	-5.58×10^{-5} [-6.04×10^{-5}, -5.11×10^{-5}]	-4.71×10^{-6} [-5.06×10^{-6}, -4.35×10^{-6}]	0.798	-6.02×10^{-5} [-6.58×10^{-5}, -5.46×10^{-5}]	-5.63×10^{-6} [-6.06×10^{-6}, -5.21×10^{-6}]	0.798
Exponential model*	3.42×10^{-5} [3.11×10^{-5}, 3.76×10^{-5}]	8.11×10^{-2} [7.39×10^{-2}, 8.84×10^{-2}]	0.799	3.92×10^{-5} [3.62×10^{-5}, 4.24×10^{-5}]	7.98×10^{-2} [7.38×10^{-2}, 8.58×10^{-2}]	0.739

* Note: R^2 for the exponential model is computed in log-space for $\log|d_{norm}|$.

temperature were effectively zero, demonstrating that both linear and exponential normalisation schemes successfully removed the temperature trend from the measurements. Using these model parameters, all measured deflections were subsequently adjusted to the reference temperature of +10 °C, yielding temperature-corrected values for comparison with elastic multilayer calculations. It should be noted that the parameters presented in Table 6 are data-driven and represent the temperature–deflection relationship for the specific dataset and monitored conditions considered in this study, and may therefore vary under different environmental, structural, or measurement conditions.

Overall, these modelling results show that temperature–deflection relationships can be accurately represented using straightforward regression formulations, enabling the normalisation of embedded-sensor measurements to a common reference temperature and raising the important question of which regression approach provides more effective temperature correction for the embedded sensors used in this study.

Agreement and accuracy

The temperature-normalised deflections were compared with ERAPave-calculated peak deflections to assess how temperature correction influences the agreement between field measurements and mechanistic calculations. In these comparisons, ERAPave analyses incorporate seasonally adjusted asphalt-layer stiffness, while loading time is interpreted through traffic-speed effective frequency to ensure consistency with field conditions. Three conditions were examined for each sensor type: (i) no temperature correction, (ii) linear temperature correction, and (iii) exponential temperature correction. For each condition, coefficients of determination and error metrics (MAE, RMSE, and NRMSE) were computed. Figures 7–9 illustrate the comparisons between sensor-measured and ERAPave-calculated peak deflections under the three correction schemes, and Table 7 summarises the corresponding accuracy metrics.

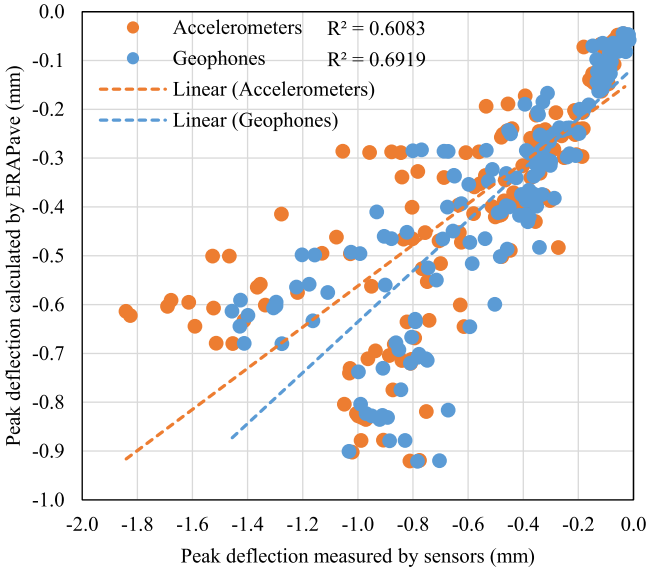

Figure 7. Comparison between sensor-measured peak deflections and ERAPave calculations without temperature correction.

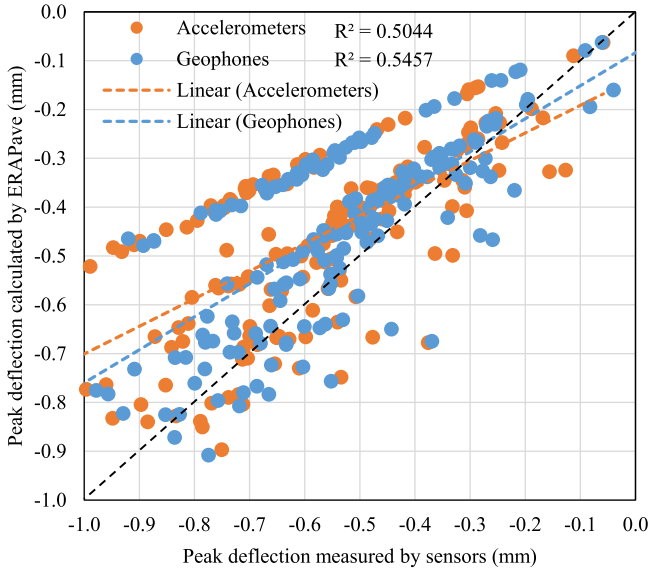

Figure 8. Comparison between sensor-measured peak deflections and ERAPave calculations after linear temperature correction.

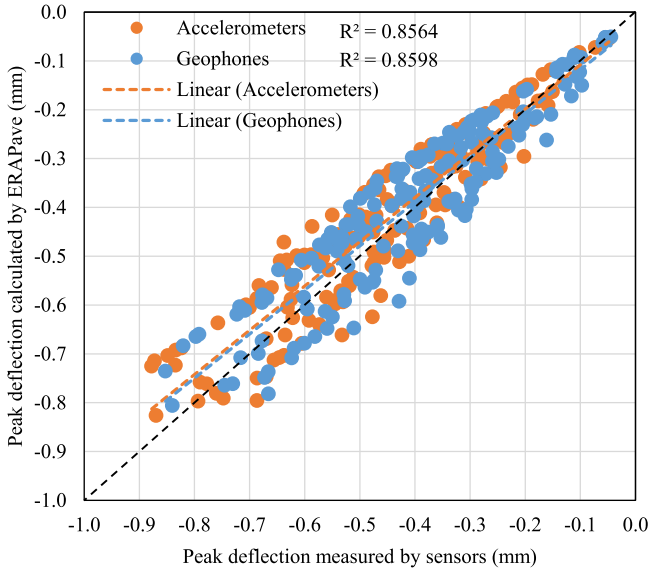

Figure 9. Comparison between sensor-measured peak deflections and ERAPave calculations after exponential temperature correction.

Table 7. Accuracy metrics for sensor-measured deflections with and without temperature correction.

	Geophone			Accelerometers		
	MAE (mm)	RMSE (mm)	NRMSE (%)	MAE (mm)	RMSE (mm)	NRMSE (%)
No correction	0.15	0.26	26.37	0.20	0.34	35.59
Linear correction	0.13	0.17	19.55	0.16	0.20	24.33
Exponential correction	0.06	0.07	9.31	0.06	0.07	9.42

For geophones, the comparison without temperature correction already showed reasonable correspondence with ERAPave-calculated deflections (Figure 7), reflecting the stability of the signal-processing procedure and the velocity-based measurement pathway, although the error metrics indicated clear room for improvement. After applying linear temperature correction (Figure 8), the agreement improved, with MAE decreasing from 0.15 mm to 0.13 mm, RMSE decreasing from 0.26 mm to 0.17 mm, and NRMSE decreasing from 26.37% to 19.55%. However, the corresponding coefficients of determination shown in Figure 8 indicate that the

linear correction reduced the goodness of fit relative to the uncorrected case. This suggests that a simple linear model was not sufficient to fully represent the temperature dependence of the measured deflections and may therefore have miscorrected conditions at the colder or warmer extremes. By contrast, the exponential correction provided better overall agreement, supporting a nonlinear temperature–deflection relationship. Applying the exponential correction (Figure 9) produced the best overall agreement, further reducing MAE to 0.06 mm, RMSE to 0.07 mm, and NRMSE to 9.31%, while increasing R^2 to 86%. These results indicate that temperature correction significantly improves the consistency between geophone-measured and ERAPave-calculated peak deflections, with the exponential model providing the greatest improvement.

Accelerometer-based deflections followed the same overall pattern, although the uncorrected results showed slightly larger discrepancies than those obtained with geophones. Without correction, MAE, RMSE, and NRMSE were 0.20 mm, 0.34 mm, and 35.59%, respectively. Linear temperature correction improved the agreement in terms of error reduction, lowering these values to 0.16 mm, 0.20 mm, and 24.33%, respectively. However, the corresponding coefficients of determination shown in Figure 8 indicate that the linear correction also reduced the goodness of fit for accelerometers, suggesting that a simple linear representation does not fully capture the nonlinear temperature dependence of asphalt stiffness and may therefore have miscorrected conditions at the colder or warmer extremes. As with the geophone measurements, the exponential correction gave the best results for accelerometers, reducing MAE to 0.06 mm, RMSE to 0.07 mm, and NRMSE to 9.42%, while increasing R^2 to 86%. Notably, after exponential correction, the accelerometer-based measurements achieved error levels comparable to those of the geophone-based measurements, indicating that accelerometer-derived deflections also follow a nonlinear temperature scaling. In addition, although both sensor types benefited substantially from exponential correction, the accelerometer-based results exhibited a relatively greater improvement in error metrics, suggesting that this formulation was particularly effective for temperature-aware correction of accelerometer-derived deflections.

The error metrics in Table 7 clearly demonstrate that temperature normalisation enhances the accuracy of both embedded sensor systems relative to elastic multilayer calculations. In both cases, the exponential correction outperformed the linear correction and yielded the lowest MAE, RMSE, and NRMSE values. Overall, these findings confirm that accounting for pavement temperature is essential for obtaining reliable agreement between measured and calculated peak deflections, and that the exponential correction approach is the most effective of the three evaluated schemes for removing thermal bias in pavement deflection measurements. This improvement is also evident in the case-wise visual comparisons shown in Figure 10, where the exponentially corrected sensor-based deflections follow the ERAPave-calculated responses more closely across all four representative cases than in the uncorrected comparisons shown previously in Figure 6. In particular, Figure 10 confirms that exponential temperature normalisation reduces the mismatch in both amplitude and overall response shape, supporting the error-metric improvements summarised in Table 7.

Discussion

This study shows that embedded geophones and accelerometers can reliably capture pavement deflections under moving heavy vehicles, while their responses are significantly influenced by pavement temperature. Statistical analyses indicate that temperature accounts for a substantial share of the variability in load-normalised deflections. As pavement temperature increases, deflection magnitudes increase consistently, reflecting the reduction in asphalt-layer stiffness. These findings confirm that temperature is the dominant environmental factor affecting embedded-sensor deflection measurements under the studied seasonal conditions.

The temperature–deflection modelling further quantifies this dependence. Both the linear and exponential formulations provided stable and physically meaningful descriptions of the temperature effect, with coefficients of determination ranging from about 0.74 to 0.80. However, the exponential model provided more effective overall temperature normalisation, consistent with the nonlinear temperature sensitivity of asphalt stiffness (National Academies of Sciences & E. & Medicine, 2024), and yielded the lowest error levels for both sensor types. Notably, accelerometer-based results showed a relatively greater improvement after exponential correction. Applying the exponential correction largely removed residual temperature-related trends. The practical added value of this correction is its direct applicability to continuous pavement-response

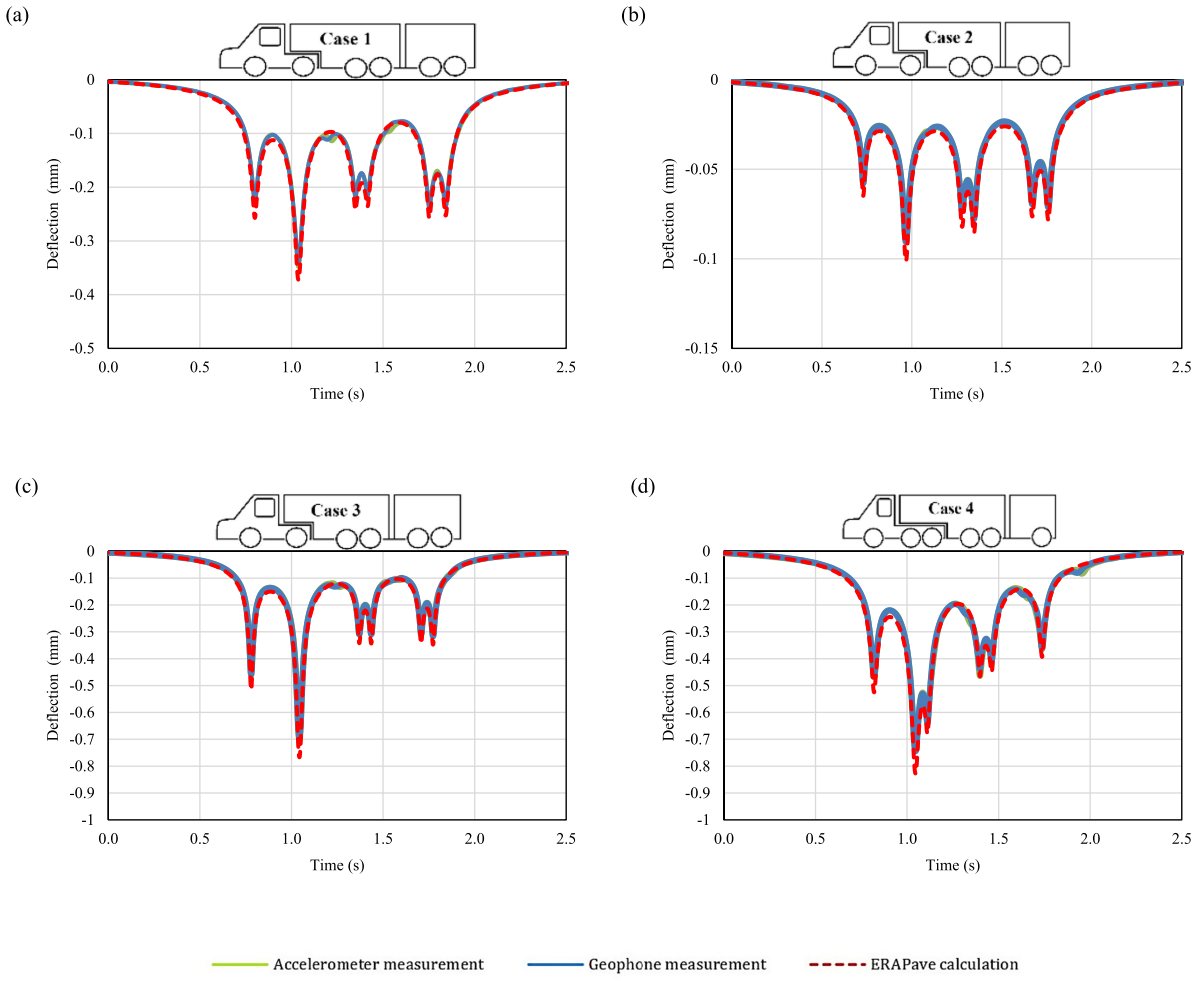

Figure 10. Comparison between exponentially temperature-corrected sensor-based deflections and ERAPave-calculated deflections for (a) Case 1 in November 2024, (b) Case 2 in February 2025, (c) Case 3 in May 2025, and (d) Case 4 in August 2025 (agreement is based on deflections corresponding to the near-surface sensor location).

measurements from embedded sensors, requiring only measured pavement temperature and sensor response and therefore remaining simple to implement for continuous field monitoring. It should also be noted that no logarithmic transformation was applied; the linear and exponential formulations were fitted directly to the measured data. The adjusted deflections also agreed more closely with ERAPave elastic multilayer calculations. ERAPave therefore provides a simplified mechanistic benchmark for evaluating the corrected responses; however, asphalt viscoelasticity, loading-frequency effects, and nonlinear behaviour of unbound materials are not explicitly represented and remain limitations of the present mechanistic comparison.

The observed exponential temperature dependence is also qualitatively consistent with the thermorheological behaviour of asphalt materials; however, the proposed correction is empirical and should not be interpreted as a formal time–temperature superposition model. Vehicle speed was accounted for during the signal-processing procedure used to derive pavement deflection but was not included as an explicit predictor in the temperature-correction model. The constant amplification assumption may not remain valid at substantially lower speeds, where loading duration and vehicle–pavement interaction may differ. Incorporating vehicle speed or an equivalent loading-frequency term may further improve the model when a wider speed range is considered.

From both mechanistic and signal-processing standpoints, the observed temperature influence reflects changes in pavement behaviour rather than changes in sensor electrical sensitivity. Asphalt modulus, damping characteristics, and the resulting pulse shape vary with temperature, whereas sensor amplification factors remain constant and should not be modified to compensate for environmental conditions. The results also highlight opportunities for further development, including evaluation of temperature-dependent curvature

outside the peak deflection region and assessment of dominant-frequency shifts as potential indicators of thermal softening. Such advances could underpin adaptive filtering and temperature-aware processing frameworks for next-generation continuous monitoring systems.

Moreover, the effect of moisture was not found to be significant in the present analysis. As noted in Table 3, moisture measurements in the unbound layers and subgrade showed only limited variation over the study period, averaging 1.6% (±0.5% SD) in the subbase and 23.3% (±1.5% SD) in the subgrade, indicating relatively stable support conditions. Accordingly, the observed variability in measured deflections was attributed mainly to temperature-dependent changes in asphalt-layer stiffness rather than to moisture-related changes in the underlying pavement structure.

Conclusion

This study evaluated how pavement temperature affects deflection measurements obtained from embedded geophones and accelerometers installed on the E16 motorway in Sweden, a cold-climate region. The analysis included heavy vehicles with axle counts ranging from two to nine, gross vehicle weights spanning 36.5 to 1311.2 kN, and speeds generally between 67.9 and 93.2 km/h. The measurements were recorded between November 2024 and August 2025 under pavement temperatures ranging from about −11 °C, with air temperatures near −19 °C, to more than 24 °C, with air temperatures above 22 °C. Across all operating conditions, pavement temperature showed a strong and systematic influence on measured deflections, demonstrating the need for explicit temperature correction in continuous pavement deflection monitoring.

Two empirical temperature–deflection correction models, linear and exponential, were developed to normalise the measured responses to a reference temperature of +10 °C. Both models effectively reduced temperature-induced variability, but the exponential formulation provided more reliable overall performance, consistent with the nonlinear temperature dependence of asphalt stiffness, with R^2 values of 80% for geophone measurements and 74% for accelerometer measurements. Comparison with ERAPave calculations further showed that temperature correction substantially improved the agreement between measured and calculated peak deflections. After exponential correction, NRMSE values were reduced to 9.31% for geophones and 9.42% for accelerometers, while R^2 increased to 0.86 for both sensor types.

Overall, the results demonstrate that embedded geophones or accelerometers, when combined with suitable signal processing and temperature normalisation, provide a practical and effective approach for year-round pavement response monitoring under traffic-speed conditions. The findings support the use of low-cost embedded vibration sensors for continuous structural monitoring in cold and seasonally variable climates. Future work should extend the monitoring period, consider additional environmental variables such as moisture and freeze–thaw effects, and explore the integration of viscoelastic or temperature-dependent processing and mechanistic models to further enhance accuracy and interpretation.

Practical implications

The findings of this study have several practical implications for pavement monitoring, structural evaluation, and the design of temperature-aware pavement monitoring systems.

- *Temperature correction is essential:* Uncorrected deflection measurements may be misinterpreted, especially in climates with large seasonal changes. Applying temperature normalisation ensures that measured variations reflect real structural behaviour rather than environmental effects.
- *Exponential correction is recommended:* While linear models are simple to use, the exponential approach provides more accurate normalisation and removes thermal bias more effectively.
- *Embedded sensors support traffic-speed assessment:* Once temperature effects are corrected, geophones or accelerometers can deliver reliable deflection estimates under real traffic.
- *Better maintenance decisions:* Temperature-normalised deflections help distinguish true pavement deterioration from seasonal stiffness changes, improving the timing and prioritisation of maintenance activities.

- *Potential for advanced temperature-aware signal processing*: Future monitoring systems may incorporate dominant-frequency shifts, pulse-shape curvatures, and temperature-dependent filtering to further improve the robustness of pavement deflection monitoring.

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Author contributions

CRediT: **Mohammad Arbabpour Bidgoli:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing; **Sigurdur Erlingsson:** Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – review & editing.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Declaration of generative artificial intelligence (GAI) tools

During the preparation of this study, the authors utilised OpenAI's ChatGPT, Microsoft's Copilot, and Google's Gemini to proofread the article, conduct a final review, and enhance its readability. Upon using these GAI-assisted tools, the authors carefully reviewed and edited the content as needed, assuming full responsibility for the publication's content.

Contribution statement

This study provides one of the first field-validated assessments of how mean near-surface pavement temperature influences pavement deflections measured by permanently embedded sensors under real heavy-vehicle loading in a cold climate region. The work introduces and evaluates both linear and nonlinear temperature-correction models, demonstrates their effectiveness using multilayer elastic calculations (ERAPave software), and establishes a practical framework for environmental normalisation in continuous pavement deflection monitoring. The findings support the development of climate-responsive PRM tools and demonstrate that low-cost embedded sensors can deliver reliable structural information year-round when temperature effects are properly addressed.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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