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DETECTION OF THE 2019 HIKURANGI SUBDUCTION ZONE SLOW SLIP EVENT USING THE TRANSFORMER DEEP LEARNING MODEL

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ARTICLE INFO	ABSTRACT
Article history: Received 18 June 2026 Accepted 25 August 2026 Available online 9 September 2026	The study of slow slip events (SSEs) is of great significance for understanding interplate coupling in subduction zones and revealing the mechanisms governing plate motion. In this study, Global Navigation Satellite System (GNSS) time series from 46 stations in the Hikurangi subduction zone, New Zealand, in 2019 were analyzed. Trend terms, periodic terms, and nonstationary deformation signals were removed to improve the signal-to-noise ratio of slow slip time series, and a Transformer-Attention model was constructed for the automatic detection of SSE occurrence intervals. The results show that, when detecting preprocessed slow slip time series, the model achieved Accuracy values higher than 0.984, Precision values higher than 0.906, Recall values higher than 0.914, and F1-score values higher than 0.948. When detecting raw GNSS time series containing other tectonic deformation signals, the model achieved Accuracy values higher than 0.953, Precision values higher than 0.903, Recall values higher than 0.707, and F1-score values higher than 0.828. These results indicate that the Transformer-Attention model can identify slow slip signals and effectively suppress interference from tectonic deformation signals. Compared with the PatchTST, BiLSTM-Attention, CNN-Attention and TCN models, the Transformer-Attention model improved R^2 by 42.5 %, 46.1 %, 53.1 %, and 54.3 %, reduced RMSE by 58.3 %, 59.8 %, 62.1 %, and 54.3 %, and reduced MAE by 68.9 %, 70.9 %, 73.3 %, and 77.9 %, respectively. Therefore, the Transformer-Attention model can effectively identify slow slip signals in GNSS time series and provide an important observational basis for investigating the spatiotemporal evolution characteristics of slow slip events.
Keywords: GNSS time series Deep learning Transformer-Attention model Slow slip events Tectonic deformation	

1. INTRODUCTION

Slow slip events (SSEs) are slow rupture or slip processes that occur on faults or plate boundaries, with durations ranging from days to months or even longer. Unlike regular earthquakes, SSEs generally do not generate obvious high-frequency seismic waves, but they can reflect stress release and deformation migration along plate interfaces through surface deformation, tremor activity, and other slow earthquake phenomena. Since the typical silent slip phenomenon in the Cascadia subduction zone was identified (Dragert et al., 2001), slow slip has gradually been regarded as an important component of slip behavior on plate interfaces. Subsequently, the identification of episodic tremor and slip (ETS) (Rogers and Dragert, 2003) further revealed the close relationship between slow slip and tremor activity. In addition, subsequent studies have shown that slow slip occurs widely in circum-Pacific subduction zones and plays an important role in studies of interplate coupling, stress release processes, and earthquake cycles (Schwartz and Rokosky, 2007).

Continuous Global Navigation Satellite System (GNSS) observation networks provide an important means of capturing surface deformation. GNSS time series can continuously record surface displacement before and after earthquakes and during interseismic periods, and can also be used to invert for fault slip distributions, constrain the locations of deformation sources, and analyze strain release processes. Using dense Global Positioning System (GPS) observations in Japan, Ozawa et al. (2011) revealed the coseismic and postseismic slip characteristics of the 2011 Mw 9.0 Tohoku earthquake, indicating the important role of GNSS in characterizing large-scale tectonic deformation and postseismic adjustment processes. Hamling et al. (2017) combined GNSS and Interferometric Synthetic Aperture Radar (InSAR) geodetic observations to reveal the complex multi-fault rupture process of the 2016 Kaikōura earthquake in New Zealand, further demonstrating that continuous geodetic observations can effectively constrain surface deformation responses under complex tectonic settings. Meanwhile, displacement signals generated by slow slip events usually have

small amplitudes and long durations, and can overlap with seasonal terms, station noise, step changes, and other tectonic deformation signals, thereby increasing the difficulty of event identification and boundary determination.

To address this issue, existing studies have gradually developed from manual identification to automatic detection. Crowell et al. (2016) used the relative strength index (RSI) method to automatically identify transient deformation in single-station GPS time series, indicating the feasibility of statistical index methods in slow slip detection. In recent years, with the rapid development of machine learning methods in complex time-series analysis, deep learning has also begun to be introduced into SSE research. Xue and Freymueller (2023) conducted transient deformation detection based on single-station GPS time series, Costantino et al. (2023) developed a deep learning detection framework for multi-station geodetic time series, and Wang et al. (2024) further achieved effective identification of slow slip events in the Cascadia region based on GNSS time series. These studies indicate that machine learning, especially deep learning, has clear potential for extracting weak deformation signals from complex backgrounds. However, existing studies are still mainly concentrated in a few well-studied regions. For observational data with significant regional differences, such as those from the Hikurangi subduction zone in New Zealand, studies of automated detection, especially those based on preprocessed multi-station three-component GNSS time series, remain relatively limited.

Therefore, to address the problems that slow slip signals are easily obscured and difficult to identify using empirical criteria, this study uses the east, north, and up displacement time series from 46 GNSS stations on the North Island of New Zealand to investigate slow slip signal detection. First, GNSS time series preprocessed by parametric decomposition were used as input, and the Transformer-Attention model was applied to detect slow slip signals and evaluate its performance in identifying slow slip signals. Second, considering the interference of tectonic deformation signals, the Transformer-Attention model was again used to detect slow slip signals and evaluate its robustness to such interference. Finally, the detection results of the Transformer-Attention model were compared with those of the Patch Time Series Transformer (PatchTST), BiLSTM-Attention, CNN-Attention and Temporal Convolutional Network (TCN) models to comprehensively evaluate the superiority of the Transformer-Attention model in detecting slow slip signals, providing an observational basis for identifying slow slip events and their evolution.

2. DATA SOURCES AND REGIONAL TECTONIC SETTING

2.1. TECTONIC SETTING AND DISTRIBUTION OF GNSS STATIONS

The North Island of New Zealand is located on the upper plate of the Hikurangi subduction zone, along the convergent boundary between the Pacific and Australian plates. This subduction zone has continued to evolve since the Oligocene and shows significant along-strike segmentation and spatial variations in deformation in terms of geometry, coupling state, and upper-plate tectonic response (Nicol et al., 2007). As a typical region for slow slip event studies, early geodetic observations in this area successfully captured slow slip signals in northern Hikurangi, confirming the occurrence of slow slip on the plate interface (Douglas et al., 2005). In addition, slow slip events in different segments of this subduction zone show clear regional differences in duration, recurrence interval, and slip depth (Wallace and Beavan, 2010), and exhibit the distinctive tectonic characteristics of coexisting shallow and deep slow slip events coexist (Wallace, 2020). Given the unique advantages of this region for testing SSE detection methods, analyzing subduction-zone deformation processes, and investigating the relationship between SSEs and interseismic coupling, this study selected the North Island of New Zealand as the study area to conduct slow slip event detection based on GNSS time series.

To characterize the regional deformation response associated with the 2019 slow slip event, this study compiled observational data from continuous GNSS stations on the North Island of New Zealand. Considering data continuity, signal quality, and spatial representativeness, 46 stations were selected from stations on the North Island and analyzed. Station locations, observation periods, and equipment-related information were mainly compiled from the station metadata dataset provided by GeoNet (<https://doi.org/10.21420/0VY2-C144>) (GNS Science, 2022), and the high-precision GNSS displacement time series were obtained from the Nevada Geodetic Laboratory, University of Nevada, Reno (<https://geodesy.unr.edu>). Figure 1 shows the distribution of GNSS stations along the eastern coast of the North Island of New Zealand. In terms of spatial distribution, these 46 GNSS stations cover the eastern coast, inland areas, and different latitudinal sections of the North Island, and can effectively reflect deformation variations along the strike of the Hikurangi subduction zone and from the near-trench region landward. These stations are located in key parts of the study area and can provide observational constraints on the overall spatial distribution of slow-slip-related deformation, thereby more clearly showing the time-series response characteristics of the 2019 slow slip event at stations (Okada et al., 2022).

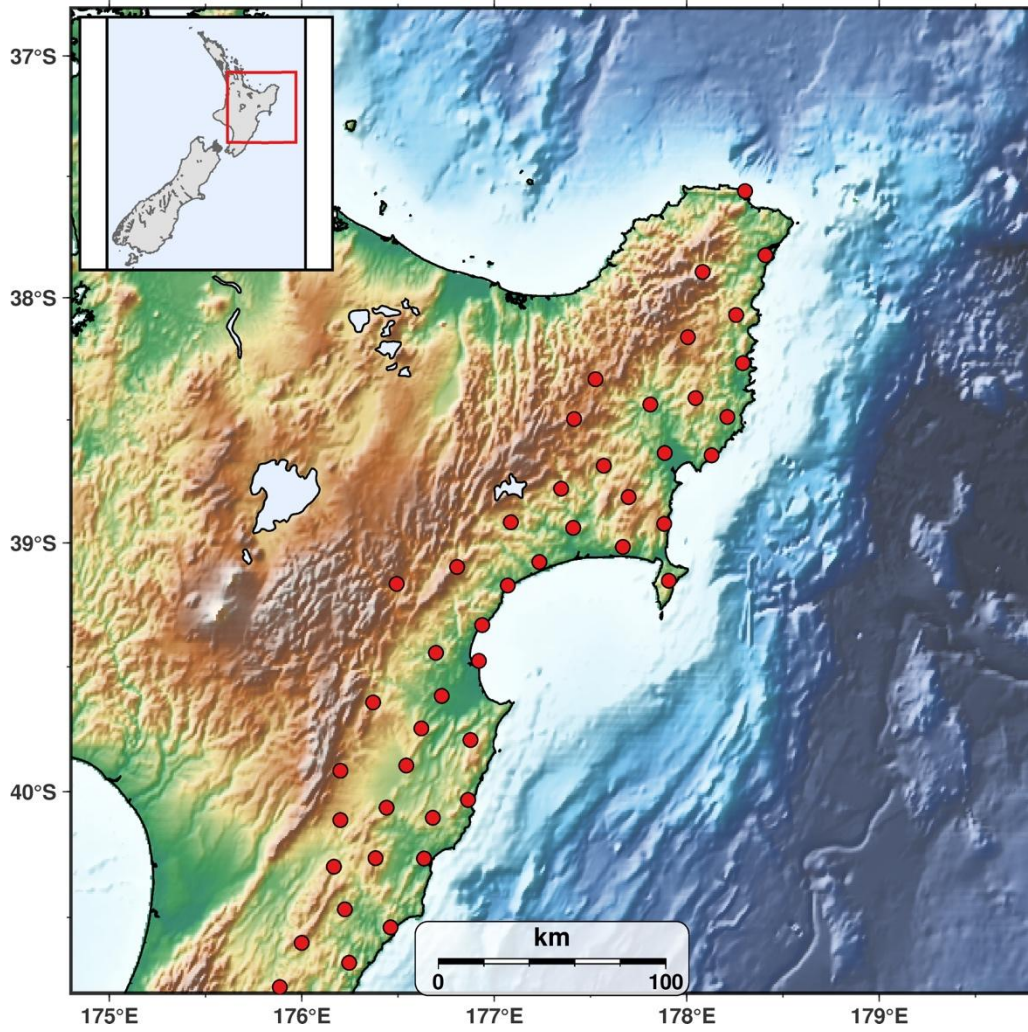


Fig. 1 GNSS stations along the eastern coast of the North Island, New Zealand. Red circles indicate the locations of the selected 46 stations.

2.2. TIME SERIES PREPROCESSING

Because GNSS time series contain multiple superimposed background components, such as long-term trends, seasonal variations, equipment-related steps, and earthquake-related disturbances, slow slip signals are often difficult to identify directly from the original series. Therefore, following the parametric decomposition approach used by the Nevada Geodetic Laboratory for GNSS processing (Blewitt et al., 2018), this study preprocessed the three-component displacement time series. The time series was modeled using the following parametric model:

$$y(t) = a_0 + a_1(t - t_0) + a_2 \sin(2\pi t) + a_3 \cos(2\pi t) + a_4 \sin(4\pi t) + a_5 \cos(4\pi t) + \sum_{k=1}^K b_k H(t - t_k) + \sum_{j=1}^J c_j H(t - t_j) + \sum_{j=1}^J d_j \left(1 - e^{-\frac{t-t_j}{\gamma}}\right) H(t - t_j) + \varepsilon(t) \quad (1)$$

In the equation, $y(t)$ represents the displacement time series in a given direction, a_0 is the constant term, and a_1 is the linear trend term, which is used to describe the long-term background motion of the

station. a_2 to a_5 represent the annual and semiannual periodic terms, which are used to characterize seasonal variations caused by hydrological loading, atmospheric loading, thermoelastic effects, and other factors. The term $\sum_{k=1}^K b_k H(t - t_k)$ represents step changes caused by equipment replacement or changes in observation conditions, modeled using the Heaviside step function. $\sum_{j=1}^J c_j H(t - t_j)$ represents the coseismic step term, and $\sum_{j=1}^J d_j (1 - e^{-(t-t_j)/\gamma}) H(t - t_j)$ represents the postseismic exponential recovery term, where γ is the postseismic decay time constant. Together, the coseismic step and postseismic recovery terms characterize the instantaneous displacement caused by earthquakes and the subsequent continuous adjustment process. $\varepsilon(t)$ represents the residual term unexplained by the model.

In the parametric decomposition of GNSS time series, a linear term was used to represent the long-term station velocity, while annual and semiannual terms were introduced to model the dominant seasonal signals, thereby reducing the interference of long-term

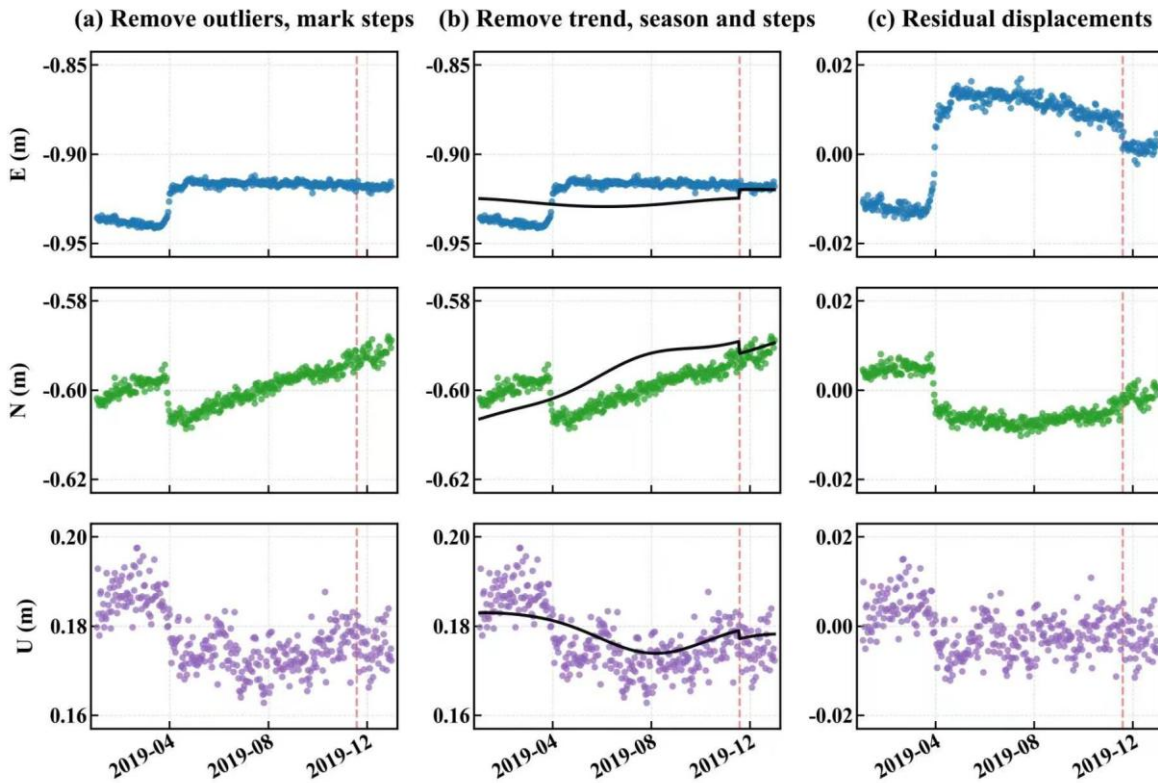


Fig. 2 GNSS time series preprocessing. (a) Original time series. (b) Fitting of the long-term trend, seasonal terms, and step terms after outlier removal. (c) Residual displacement time series after removing the steady-state background and step terms. Blue dots represent the east-component displacement time series, green dots represent the north-component displacement time series, and purple dots represent the up-component displacement time series. The red dashed lines indicate the equipment step dates, and the black lines represent the fitted background signals.

tectonic motion and seasonal variations in the identification of transient slow slip deformation (Klos et al., 2018; Bawa, 2019; Nistor et al., 2021). On this basis, earthquake-related signals were modeled and corrected. In earthquake event screening, this study set an epicentral distance threshold of 300 km and retained only near-field or intermediate- to far-field events with potential physical impacts on the target stations for modeling (Dong et al., 2025). For short-term postseismic decay and transient deformation evolution, an empirical decay time constant of 60 d was adopted for the postseismic recovery term, and exponential and logarithmic functions were used to approximate the nonlinear characteristics of GNSS postseismic signals (Okada and Nishimura, 2025; Xiang et al., 2023). To enhance the robustness of baseline model fitting, observational uncertainties and the median absolute deviation (MAD) were incorporated during the time-series preprocessing as multiple quality-control criteria. Through multi-stage data cleaning and outlier removal, stable background model parameters and residual time series were finally obtained using iterative least squares (Cucci et al., 2023; Peidou et al., 2023; Mastella et al., 2025; Ohta and Ohtate, 2026; Birinci and Saka, 2026). The overall workflow of time series preprocessing is shown in Figure 2 using the GISB station as an example.

3. METHODOLOGY

3.1. SIMULATION OF SLIP SIGNALS

Due to the scarcity of observational samples of real slow slip events, it is difficult to meet the training requirements of deep learning models. Therefore, this study expanded the training data by constructing simulated samples based on the characteristics of shallow slow slip events in Hikurangi. A slow slip simulation sample set based on preprocessed residual terms was constructed. Before slow slip event detection and simulation analysis, missing values in the GNSS time series were handled and background components were removed (Qiu et al., 2024; Ji et al., 2024; Mastella et al., 2025). To avoid the influence of slow slip events on the simulated background, long-term residual time series from 46 continuous stations were selected as candidate background segments. During background selection, periods corresponding to slow slip events, segments with obvious step changes, and windows with poor data continuity were excluded. The residual backgrounds were finally screened using threshold criteria (R Core Team, 2025). On this basis, according to the preset event start time, duration, and three-component displacement amplitudes, slow slip deformation signals were synthesized using a hyperbolic tangent function to

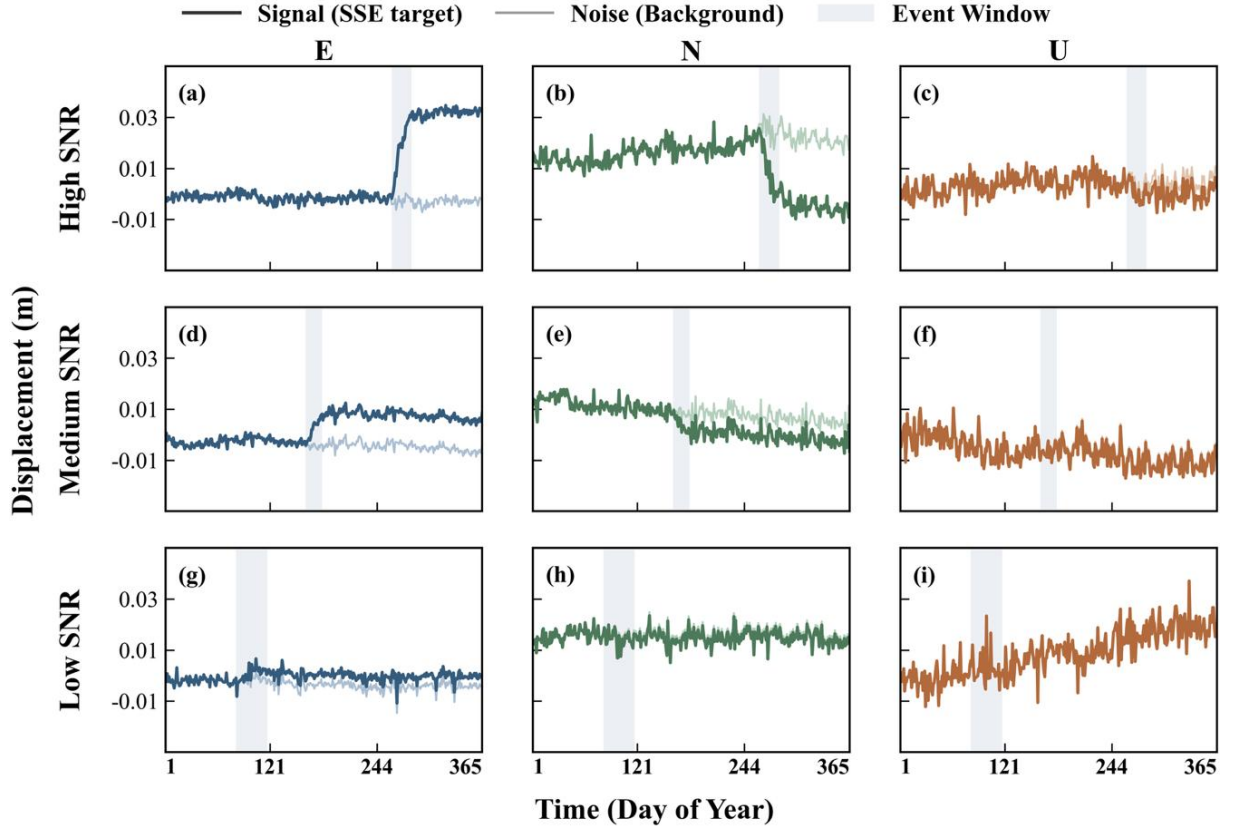


Fig. 3 Examples of GNSS time series containing target slow slip event (SSE) signals and background noise with different signal-to-noise ratios (SNRs) and event start times. The dark solid lines represent the time series with superimposed SSE signals, the light solid lines represent the corresponding background noise sequences, and the light-blue shaded areas indicate the labeled SSE time windows. Panels (a), (d), and (g) show the E-component time series; panels (b), (e), and (h) show the N-component time series; and panels (c), (f), and (i) show the U-component time series.

simulate slow slip events. The hyperbolic tangent function (Brudzinski et al., 2007; Correa-Mora et al., 2008) is parameterized as follows:

$$u(t) = \frac{A}{2} \left[\tanh\left(\frac{t-t_0}{\tau}\right) + 1 \right] \quad (2)$$

where $u(t)$ denotes the simulated displacement at epoch t , A is the final cumulative slip amplitude of the slow slip event, t_0 represents the central epoch of the event, and τ is the time-scale parameter controlling the slip rate and event duration.

Finally, the synthetic slow-slip signal was superimposed on the screened residual backgrounds from real observations to generate simulated slow-slip time-series samples. The corresponding simulated time series without slow slip retained only the same type of residual background and were used as non-event samples. Based on the characteristics of shallow slow slip events in Hikurangi, the simulated dataset was constructed with event durations of approximately 2–6 weeks, maximum cumulative slip ranging from several centimeters to 25 cm, and simulated cumulative horizontal GNSS displacements of 0.8–5.0 cm. The event start time was randomly assigned within each 365-day time series. Different signal-to-noise ratios (SNRs) were also introduced to simulate variations in SSE signal strength relative to the GNSS

background. The simulated slow-slip time series are shown in Figure 3.

3.2. TRANSFORMER-ATTENTION MODEL

The Transformer-Attention model consists of a Transformer, a channel attention module (Yarce et al., 2019; Ikari et al., 2020; Yan et al., 2023; Woods et al., 2024) mechanism module, and a spatial attention mechanism module, as shown in Figure 4(a). The overall model is composed sequentially of a linear projection layer, a positional encoding layer, a Transformer encoder, a channel attention module, a spatial attention module, and an output layer. The model takes three-component GNSS time series as input and maps them into a 64-dimensional embedding space through a linear layer. Figure 4(b) shows the internal structure of the Transformer Encoder, which consists of four encoder layers and four attention heads. The feed-forward network dimension is 128, the activation function is the rectified linear unit (ReLU), and the dropout rate is set to 0.1. The channel attention and spatial attention modules are shown in Figures 4(c) and 4(d), respectively. The model contains 137,543 trainable parameters. During training, the binary cross-entropy with logits loss (BCEWithLogitsLoss) and the Adam optimizer were used, with an initial learning rate of

1×10^{-3} , a batch size of 128, and a maximum of 100 training epochs. The learning rate was adjusted using the ReduceLROnPlateau strategy and was reduced by a factor of 0.1 when the validation loss did not improve for five consecutive epochs. Let the input residual sequence be denoted as $X = \{\mathbf{x}_t\}_{t=1}^T$, where $\mathbf{x}_t = [E_t, N_t, U_t]$ represents the eastward, northward, and vertical residual components at time t , and T is the sequence length. The three-component joint input was adopted instead of independent modeling of each direction, mainly because the response amplitudes and significance of surface deformation caused by slow slip are not completely consistent among different directions. Multivariate joint modeling is more conducive to preserving complementary information among directions and enhancing the representation of weak signals (Su et al., 2025).

To make the original three-component observations suitable for subsequent high-dimensional time-series feature extraction, the input sequence first undergoes linear mapping:

$$\mathbf{Z}_0 = \mathbf{X}\mathbf{W}_e + \mathbf{b}_e \quad (3)$$

where $\mathbf{W}_e$ and $\mathbf{b}_e$ are learnable parameters. Subsequently, the positional encoding $\mathbf{PE}$ is added to the mapped sequence representation, yielding

$$\mathbf{Z} = \mathbf{Z}_0 + \mathbf{PE} \quad (4)$$

This process corresponds to the “Linear” and “PE” parts in Figure 4(a). These two structures explicitly inject temporal order information into the feature space. Since slow slip signals have clear persistence and stage-dependent characteristics, effective discrimination is difficult to achieve by relying only on instantaneous amplitudes. The model must also identify the relative position of a certain change in the preceding and following background and its temporal relationship. Therefore, positional encoding is an important prerequisite for subsequent time series modeling (Su et al., 2025).

The feature sequence after positional encoding is subsequently input into the Transformer encoder for global time series feature extraction. Its structure is shown in Figure 4(b), and it consists of multi-head self-attention, residual connection and normalization, and a feed forward network. The encoding process can be written as

$$\mathbf{H} = \text{TransformerEncoder}(\mathbf{Z}) \quad (5)$$

Transformer was adopted as the backbone module because slow slip events do not appear as strong, short-duration abrupt changes, but are mainly manifested as gradual offsets, continuous accumulation over a relatively long-time scale, and overall differences from background segments. Compared with traditional convolutional structures that mainly rely on local receptive fields, Transformer can directly establish dependencies between any two temporal positions through the self-attention mechanism.

After obtaining the global temporal feature $\mathbf{H}$, this study further introduces a channel attention module to adaptively recalibrate the feature channels, and its structure corresponds to Figure 4(c). Specifically, the model first performs average pooling and max pooling on the input features, then generates channel weights through a shared multi-layer perceptron and a Sigmoid activation function, and broadcasts them to the original features for reweighting. This process can be expressed as

$$\mathbf{M}_c = \sigma(f_c(\mathbf{H})) \quad (6)$$

$$\mathbf{H}_c = \mathbf{M}_c \odot \mathbf{H} \quad (7)$$

where $\mathbf{M}_c$ represents the channel weights, and $\odot$ denotes element-wise multiplication. This process enhances the high-dimensional feature channels formed after linear mapping and Transformer encoding. The function of this module is to highlight features combinations across directions and temporal evolution patterns that are sensitive to slow slip detection from high-level temporal representations, while suppressing noise-dominated feature responses or those that contribute less to detection, thereby increasing the proportion of effective information in subsequent discrimination.

After channel enhancement, the model further introduces a spatial attention module to identify key time intervals, and its structure is shown in Figure 4(d). The spatial attention mechanism models the importance of positions along the one-dimensional temporal axis. This module performs average pooling and max pooling on $\mathbf{H}_c$, generates a temporal attention distribution through convolution and Sigmoid activation, and reweights the feature sequence:

$$\mathbf{M}_s = \sigma(f_s(\mathbf{H}_c)) \quad (8)$$

$$\mathbf{H}_s = \mathbf{M}_s \odot \mathbf{H}_c \quad (9)$$

where $\mathbf{M}_s$ represents the temporal attention weights. Since slow slip events usually occur only in local intervals of the sequence, while a large number of time points correspond to non-event backgrounds, the model needs to know not only “which features are more important” but also “which time periods deserve more attention”. By introducing spatial attention, the model can further improve its response capability to potential slow slip occurrence intervals and weaken the dilution effect of long background segments on event discrimination.

Finally, as shown on the right side of Figure 4(a), the attention-enhanced high-level features are passed through normalization and a fully connected layer to output the probability of slow slip occurrence at each time point. If $h_{s,t}$ denotes the high-level feature vector corresponding to the time point t , the model output can be written as

$$p_t = \sigma(\mathbf{W}_o h_{s,t} + b_o) \quad (10)$$

where $p_t \in [0,1]$ represents the predicted probability that the time point t belongs to a slow slip event.

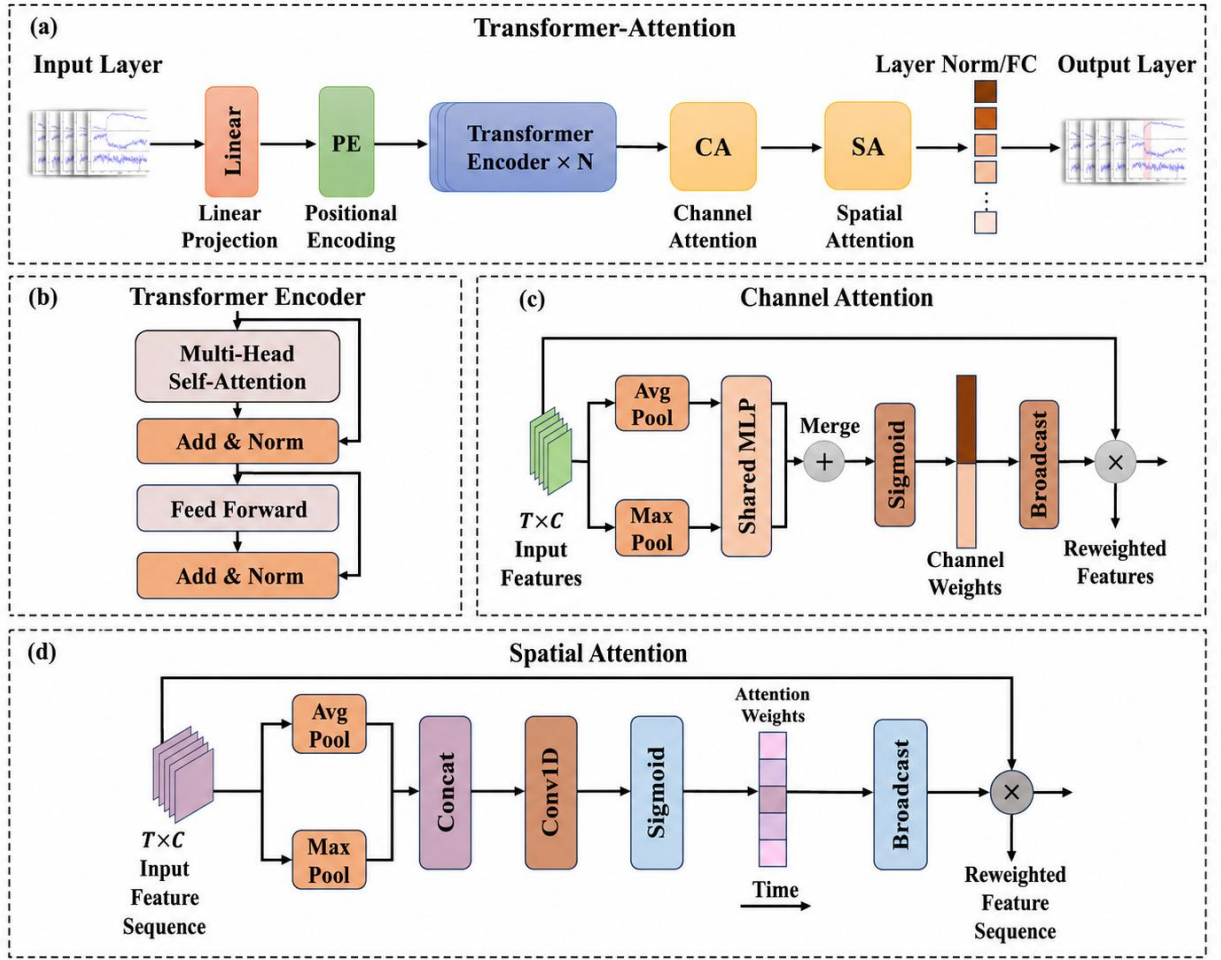


Fig. 4 (a) Transformer-Attention model, in which the attention mechanisms include channel attention and spatial attention to enhance spatiotemporal feature learning; (b) internal structure of the Transformer; (c) channel attention mechanism; and (d) spatial attention mechanism.

Furthermore, the probability sequence is converted into binary labels using the threshold τ .

$$\hat{y}_t = \begin{cases} 1, & p_t \geq \tau \\ 0, & p_t < \tau \end{cases} \quad (11)$$

3.3. EVALUATION METRICS

To quantitatively evaluate the detection performance of the Transformer-Attention model on slow slip events, this study formulated slow slip event detection as a binary classification problem and calculated classification performance metrics based on the confusion matrix, using common performance evaluation metrics for anomaly detection. The evaluation metrics include Accuracy, Precision, Recall, and F1 score. The evaluation metrics are calculated as follows:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (12)$$

$$Precision = \frac{TP}{TP+FP} \quad (13)$$

$$Recall = \frac{TP}{TP+FN} \quad (14)$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (15)$$

True positives (TP) represent the slow slip time points correctly identified by the model, false positives (FP) represent non-slow-slip time points incorrectly classified by the model as events, false negatives (FN) represent real event time points that are not identified by the model, and true negatives (TN) represent nonevent time points correctly identified by the model. Accuracy reflects the overall classification correctness of the model and is defined as the proportion of correctly predicted samples among all samples. Precision represents the proportion of real events among the samples identified by the model as slow slip events, reflecting the reliability of the model prediction results. Recall represents the proportion of successfully identified samples among all real slow slip event samples, reflecting the detection ability of the model for real events. The F1 score provides a more balanced assessment of the overall performance of the model in both false alarm control and event detection.

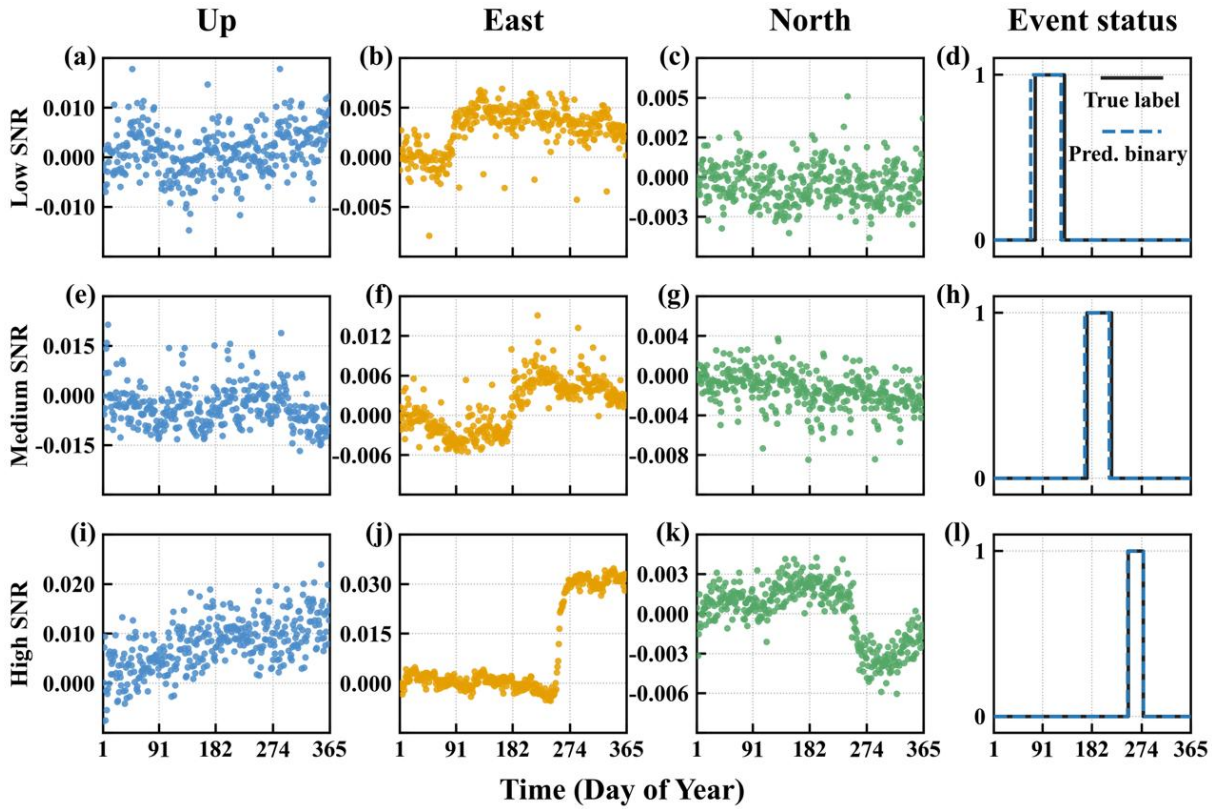


Fig. 5 (a), (e), and (i) simulated U-component time series with different SNRs; (b), (f), and (j) simulated E-component time series with different SNRs; (c), (g), and (k) simulated N-component time series with different SNRs; and (d), (h), and (l) detection results for the test data with different SNRs.

4. RESULTS AND DISCUSSION

4.1. DETECTION RESULTS OF SIMULATED SLOW SLIP TIME SERIES

The simulated samples were partitioned independently by GNSS station (Tanaka et al., 2025). A total of 20,000 simulated samples were generated and divided into training, validation, and test sets at a ratio of 70:15:15, containing 14,000, 3,000, and 3,000 samples, respectively (Gou et al., 2023). After all model parameters and the detection threshold had been determined, the threshold selected using the validation set was applied to the test set for independent detection. slip signal detection experiments were then conducted on the simulated test set. The Transformer-Attention model can effectively distinguish samples containing slow slip transients from background noise containing only background disturbances. As shown in Figures 5(d), 5(h), and 5(l), in the detection of slow slip signals, the event intervals predicted by the model are generally consistent with the true labels. Although the predicted intervals show slight outward expansion at the start and end boundaries of events in individual samples, no obvious missed detections are observed overall, indicating that the model has high completeness in event detection. In contrast, for background noise, the model output remains at a low level overall, without large-scale continuous false alarms, indicating that it has a certain ability to suppress background noise disturbances and

maintain stable discrimination. Taking the simulated slow slip time series of three stations with different signal-to-noise ratios as examples, the Accuracy, Precision, Recall, and F1 values in Figure 5(d) are 0.962, 0.857, 0.889, and 0.873, respectively; those in Figure 5(h) are 0.978, 0.911, 0.911, and 0.911, respectively; and those in Figure 5(l) are 0.998, 0.966, 1.000, and 0.982, respectively, indicating that the model has good slip signal detection performance.

4.2. DETECTION RESULTS OF THE 2019 HIKURANGI SLOW SLIP EVENT

This study analyzed the time series from 46 GNSS stations in the Hikurangi subduction zone, New Zealand, in 2019, and compared the model-detected intervals with an existing slow slip catalog (Yan et al., 2023) to evaluate the stability and accuracy of the model in real-world applications. Taking the three-component GNSS coordinate time series of the CNST, GISB, and MAKO stations as examples, the detection results are shown in Figures 6(d), 6(h), and 6(l). The Accuracy values obtained by the Transformer-Attention model were 0.984, 0.984, and 0.986, respectively; the Precision values were 0.948, 0.906, and 1.000, respectively; the Recall values were 0.948, 1.000, and 0.914, respectively; and the F1-score values were 0.948, 0.951, and 0.955, respectively. The results show that the overall detection performance is satisfactory.

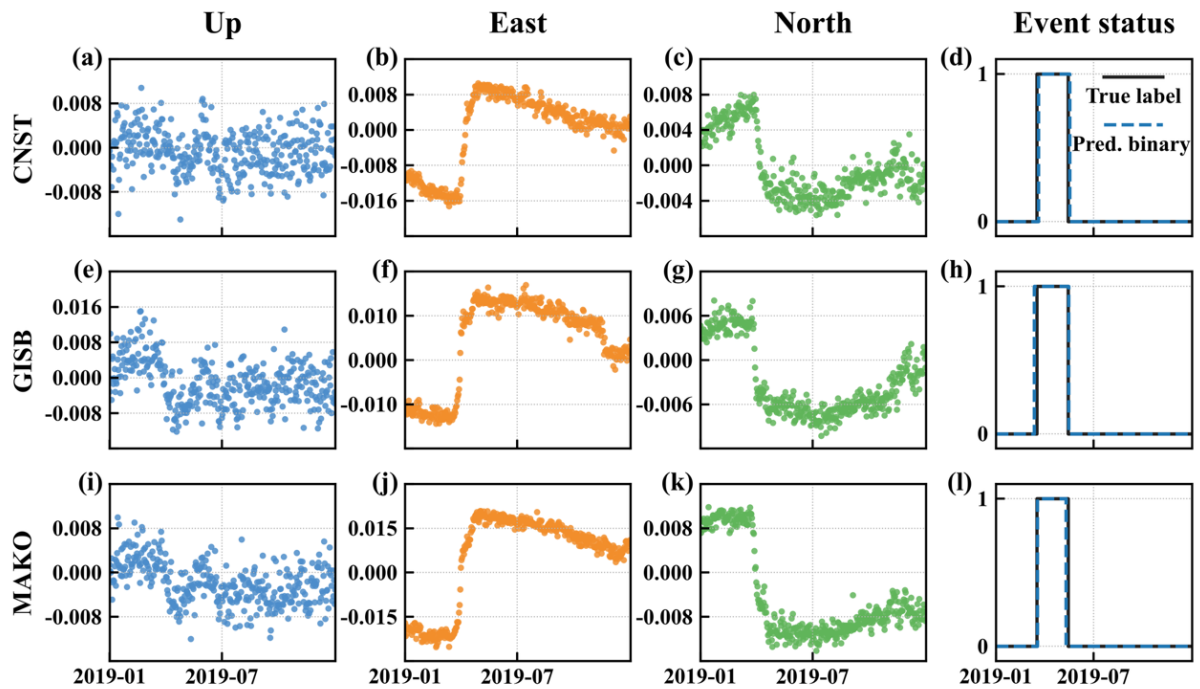


Fig. 6 (a), (e), and (i) U-component time series at different stations; (b), (f), and (j) E-component time series at different stations; (c), (g), and (k) N-component time series at different stations; and (d), (h), and (l) detection results.

Table 1 Comparison of model performance in detecting slow slip event using raw and preprocessed data at different stations.

Station	Time series data	True positives	False positives	Precision	Accuracy	Recall	F1-score
CNST	Raw	44	0	1.000	0.962	0.759	0.863
	Preprocessed	55	3	0.948	0.984	0.948	0.948
GISB	Raw	41	0	1.000	0.953	0.707	0.828
	Preprocessed	58	6	0.906	0.984	1.000	0.951
MAKO	Raw	56	6	0.903	0.989	0.966	0.932
	Preprocessed	53	0	1.000	0.986	0.914	0.955

To further verify the detection stability and adaptability of the Transformer-Attention model under conditions with and without interference from tectonic deformation signals, this study compared the detection performance when the raw and preprocessed time series were used as model inputs. Taking the CNST, GISB, and MAKO stations as examples, the Transformer-Attention model was used to detect slow slip signals, and its detection performance was evaluated. The results are shown in Table 1. For the raw time series containing interference from tectonic deformation signals, the model still showed satisfactory slow slip signal detection performance, with a mean Recall of 0.811 and a mean F1-score of 0.874 across the three stations. For the preprocessed time series without interference from tectonic deformation signals, the improvements at the CNST and GISB stations were mainly reflected in reduced missed detections. At the GISB station, the Recall reached 1.000, indicating that no false negatives occurred in this case and reflecting the high detection

sensitivity of the model; however, the Precision was 0.906, indicating the presence of false positives. At the MAKO station, the improvement was mainly reflected in the suppression of false detections. This comparison indicates that preprocessing can effectively enhance the distinguishability of weak slow slip signals, thereby improving detection accuracy and result stability. Overall, the Transformer-Attention model can effectively and stably identify slow slip signals.

4.3. COMPARATIVE ANALYSIS OF DIFFERENT DETECTION MODELS

To verify the satisfactory performance of the Transformer-Attention model in detecting slip signals, this study used the time series from the CNST, GISB, and MAKO stations as examples and compared the slow slip signal detection results of the Transformer-Attention, PatchTST, BiLSTM-Attention, CNN-Attention, and TCN models. For the PatchTST model, the Accuracy values were 0.921, 0.929, and 0.932, respectively; the Precision values were 1.000, 1.000,

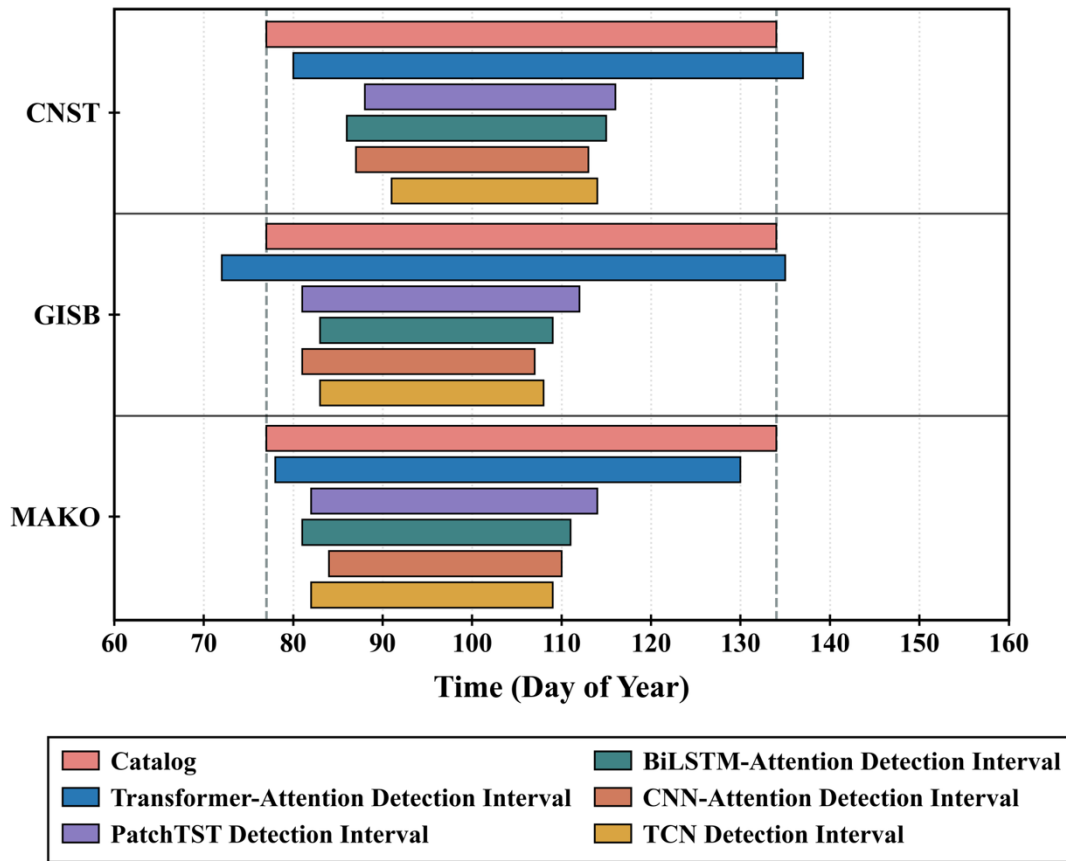


Fig. 7 Comparison of detection intervals among different models.

and 1.000, respectively; the Recall values were 0.500, 0.552, and 0.569, respectively; and the F1-score values were 0.667, 0.711, and 0.725, respectively. For the BiLSTM-Attention model, the Accuracy values were 0.923, 0.915, and 0.926, respectively; the Precision values were 1.000, 1.000, and 1.000, respectively; the Recall values were 0.517, 0.466, and 0.534, respectively; and the F1-score values were 0.682, 0.635, and 0.697, respectively. For the CNN-Attention model, the Accuracy values were 0.915, 0.915, and 0.915, respectively; the Precision values were 1.000, 1.000, and 1.000, respectively; the Recall values were 0.466, 0.466, and 0.466, respectively; and the F1-score values were 0.635, 0.635, and 0.635, respectively. For the TCN model, the Accuracy values were 0.907, 0.912, and 0.918, respectively; the Precision values were 1.000, 1.000, and 1.000, respectively; the Recall values were 0.414, 0.448, and 0.483, respectively; and the F1-score values were 0.585, 0.619, and 0.651, respectively. The comparison between the detection intervals of each model and the catalog-labeled intervals is shown in Figure 7, and the comparison of model detection performance is shown in Figure 8. Compared with the PatchTST (Nie et al., 2023), BiLSTM-Attention (Wang et al., 2024), CNN-Attention, and TCN (Lea et al., 2017) models, the Transformer-Attention model achieved increases in R^2 of 42.5 %, 46.1 %, 53.1 %, and 54.3 %, respectively; reductions in RMSE of 58.3 %, 59.8 %, 62.1 %, and 62.4 %, respectively; and reductions in

MAE of 68.9 %, 70.9 %, 73.3 %, and 77.9 %, respectively. Meanwhile, the detection performance at each station was further analyzed, as shown in Table 2. PatchTST, BiLSTM-Attention, CNN-Attention, and TCN all showed high Precision without producing false positives but also exhibited relatively obvious missed detections. This indicates that these models tended to classify slow slip signals with relatively high signal-to-noise ratios as positive samples, while their ability to detect signals with relatively low signal-to-noise ratios was limited. In summary, the quantitative evaluation indicates that the Transformer-Attention model can more accurately detect weak deformation signals associated with slow slip events in GNSS time series. This helps to identify the temporal evolution and duration of surface deformation caused by slow slip.

The slow slip occurrence intervals detected by the Transformer-Attention model are generally consistent with the cataloged intervals, indicating that the model has good performance in detecting slow slip signals. Deep learning models can facilitate the detection of slow slip signals and the investigation of their relationship with regional seismicity. Before the 2019 Hikurangi slow slip event, the earthquake occurrence rate along the eastern coast of the North Island was below 2 events per day. During the active phase of the slow slip event, seismicity increased markedly, reaching a maximum of approximately 6.5 events per day and showing a pronounced increase in

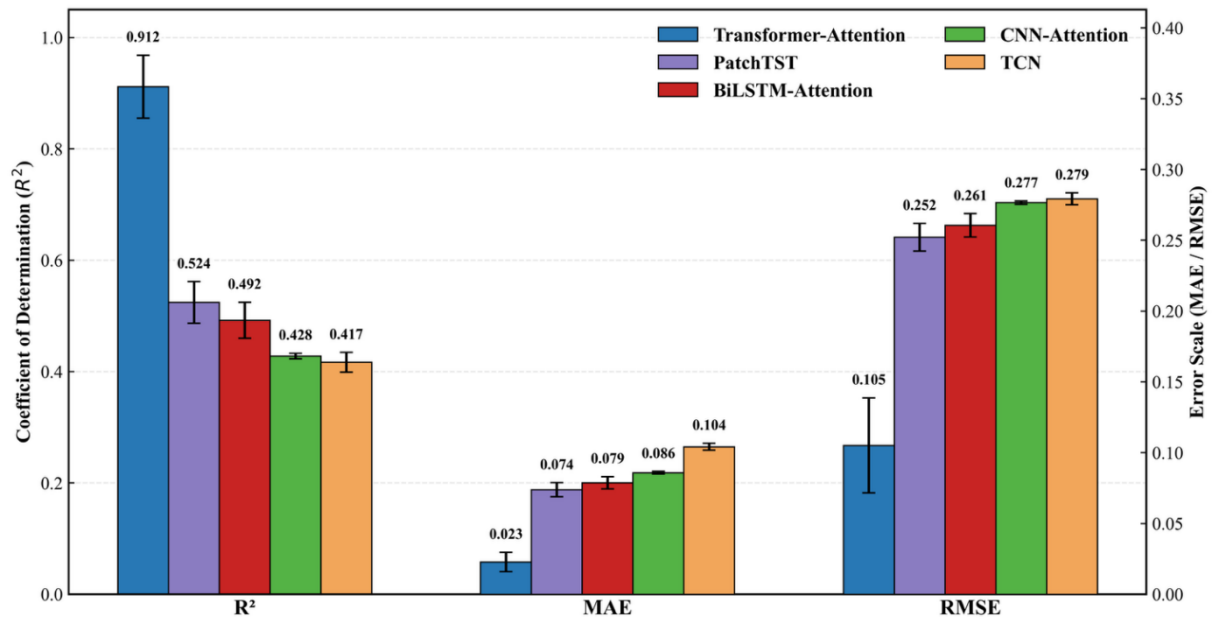


Fig. 8 Comparison of model performance.

Table 2 Comparison of detection performance of different models for slow slip event.

Station	Model	True positives	False positives	Precision	Accuracy	Recall	F1-score
CNST	PatchTST	29	0	1.000	0.921	0.500	0.667
	BiLSTM-Attention	30	0	1.000	0.923	0.517	0.682
	CNN-Attention	27	0	1.000	0.915	0.466	0.635
	TCN	24	0	1.000	0.907	0.414	0.585
GISB	PatchTST	32	0	1.000	0.929	0.552	0.711
	BiLSTM-Attention	27	0	1.000	0.915	0.466	0.635
	CNN-Attention	27	0	1.000	0.915	0.466	0.635
	TCN	26	0	1.000	0.912	0.448	0.619
MAKO	PatchTST	33	0	1.000	0.932	0.569	0.725
	BiLSTM-Attention	31	0	1.000	0.926	0.534	0.697
	CNN-Attention	27	0	1.000	0.915	0.466	0.635
	TCN	28	0	1.000	0.918	0.483	0.651

the main slip area. As the slow slip event ended, the earthquake occurrence rate decreased again to below 2 events per day (Yan et al., 2023). This pattern of low seismicity, marked increase, and subsequent decline temporally corresponds to the slow slip event observed by GNSS, reflecting transient aseismic slip along the plate interface and the associated stress redistribution during the slow slip event (Yarce et al., 2019). These results indicate that identifying the occurrence intervals of slow slip using the Transformer-Attention model can help capture transient deformation processes in subduction zones from continuous GNSS observations and, together with variations in seismicity, facilitate investigation of the relationship between slow slip and regional earthquake activity, thereby providing reliable observational evidence for seismic and geological hazard monitoring and regional risk assessment

5. CONCLUSION

This study preprocessed GNSS time series data through parametric decomposition and uses the Transformer-Attention deep learning model to detect slow slip signals, thereby evaluating the model's ability to identify slow slip signals. Using the displacement time series in the east, north, and vertical directions from 46 GNSS stations in the Hikurangi subduction zone, New Zealand, in 2019 as examples, the Transformer-Attention model was applied to detect slow slip signals at each station, and its performance in slow slip signals detection was investigated. The following conclusions were obtained:

(1) the 2019 GNSS time series in the Hikurangi region were analyzed study object. Long-term trends, periodic variations, and nonstationary deformation signals were removed through modeling, and residual time series related to slow slip were extracted. The

results show that the residual sequences can effectively preserve the characteristic information of slow slip and improve the signal-to-noise ratio of slow slip time series.

(2) this study took the CNST, GISB, and MAKO stations in the Hikurangi region as examples and used the Transformer-Attention model to detect slow slip signals. The detection Accuracy values of the model at the CNST, GISB, and MAKO stations were 0.984, 0.984, and 0.986, respectively; the Precision values were 0.948, 0.906, and 1.000, respectively; the Recall values were 0.948, 0.906, and 1.000, respectively; and the F1 score values were 0.948, 0.951, and 0.955, respectively. These results indicate that the Transformer-Attention model has satisfactory performance in detecting slow slip signals. Meanwhile, for the raw GNSS time series at the CNST, GISB, and MAKO stations containing complex tectonic deformation signals, the Precision values of the model were 1.000, 1.000, and 1.000, respectively; the Accuracy values were 0.962, 0.953, and 0.989, respectively; the Recall values were 0.759, 0.707, and 0.966, respectively; and the F1 score values were 0.863, 0.828, and 0.932, respectively. These results indicate that the Transformer-Attention model has a certain robustness to interference from tectonic deformation signals.

(3) To further analyze the detection performance of different models for slow slip signals, this study compared the detection results of the Transformer-Attention, PatchTST, BiLSTM-Attention, CNN-Attention and TCN models. Taking the time series of the CNST, GISB, and MAKO stations as examples, the R^2 of the Transformer-Attention model for detecting slow slip signal detection increased by 42.5 %, 46.1 %, 53.1 %, and 54.3 %, compared with the PatchTST, BiLSTM-Attention, CNN-Attention and TCN models, respectively, the RMSE decreased by 58.3 %, 59.8 %, 62.1 % and 62.4 %, respectively, and the MAE decreased by 68.9 %, 70.9 %, 73.3 %, and 77.9 %, respectively, indicating that the Transformer-Attention model has better performance in slow slip signal detection.

This study verified the feasibility of using deep learning models to detect slow slip signals. By using preprocessed GNSS time series, the occurrence intervals of slow slip events can be identified to a certain extent. This study provides an observational basis for understanding interplate coupling in subduction zones during slow slip, analyzing stress transfer induced by slow slip, and investigating the relationship between activity in adjacent seismogenic zones and the earthquake cycle. However, due to the limited number of real slow slip time-series samples, uncertainties in label construction, and large differences in the duration and morphology of different events, the ability of current deep learning models to detect slow slip signals under complex background conditions still has room for further improvement.

6. DATA AVAILABILITY

The high-precision GNSS displacement time series data used in this study were obtained from the Nevada Geodetic Laboratory (NGL), University of Nevada, and are available through its official website (<https://geodesy.unr.edu>). Information on continuous GNSS stations in New Zealand, station metadata, and related geoscientific data were obtained from GeoNet and are available through the GeoNet data platform (<https://www.geonet.org.nz/data/types/geodetic>). The processing of simulated data in this study was performed using R, version 4.5.2, which is available from the official R Project website (<https://www.r-project.org/>).

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