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DEVELOPMENT OF AN INTELLIGENT DEFORMATION MONITORING AND EARLY-WARNING FRAMEWORK FOR HYDRAULIC STRUCTURES USING GNSS, INSAR, AND MACHINE LEARNING

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Abstract
Progressive settlement, horizontal displacement, differential movement, foundation deformation, and seasonal structural response are important indicators of the operational condition of dams and other hydraulic structures. Conventional monitoring instruments provide accurate observations at selected points but may not adequately represent spatial deformation across large structures, while satellite-based interferometric synthetic aperture radar offers broad-area coverage but measures displacement primarily along the radar line of sight and can be affected by atmospheric disturbance, temporal decorrelation, vegetation, and data gaps. This study develops an integrated intelligent framework for deformation monitoring and early warning by combining Global Navigation Satellite System observations, satellite InSAR time series, environmental and operational variables, and machine-learning prediction. GNSS data provide continuous three-dimensional displacement at critical control points, whereas InSAR measurements map spatial settlement and differential deformation across the structure and surrounding foundation. The datasets are temporally synchronized, geometrically transformed into common displacement components, filtered for outliers and atmospheric noise, and fused using uncertainty-based weighting. A hybrid gated recurrent unit-attention model is proposed to forecast short-term deformation by learning nonlinear relationships among previous displacement, reservoir level, water temperature, air temperature, rainfall, and time-dependent structural response. The framework also includes anomaly detection based on displacement magnitude, deformation velocity, acceleration, residual error, spatial inconsistency, and persistence of abnormal behaviour. A multilevel early-

warning index classifies structural response into normal, attention, warning, and critical states. The methodology is demonstrated through a representative hydraulic-structure monitoring scenario rather than a certified dataset from a specific dam. The expected contribution is a transparent decision-support system that combines point-scale accuracy, spatial coverage, short-term prediction, and engineering interpretation. The proposed framework can support targeted inspection, additional instrumentation, operational adjustment, maintenance planning, and timely intervention before progressive deformation develops into a major safety problem.

Keywords: Hydraulic structures; dam deformation; GNSS monitoring; interferometric synthetic aperture radar; Sentinel-1; data fusion; gated recurrent unit; attention mechanism; anomaly detection; early warning.

Introduction

Hydraulic structures are exposed to complex and time-dependent actions arising from hydrostatic pressure, temperature variation, foundation consolidation, material creep, seasonal moisture changes, sediment loading, seismic effects, construction defects, and deterioration of structural or drainage components. These actions may produce vertical settlement, horizontal displacement, differential deformation, rotation, joint opening, cracking, and localized instability. Small displacement does not automatically indicate an unsafe condition because some deformation may represent normal elastic, thermal, or consolidation response; however, a persistent change in deformation rate, spatially uneven settlement, non-recoverable movement, increasing acceleration, or loss of correlation with known environmental loading may indicate abnormal behaviour. Reliable safety assessment therefore requires more than comparison of a measured displacement with one fixed threshold. The magnitude, direction, rate, acceleration, spatial pattern, duration, measurement uncertainty, and relationship with reservoir and climatic conditions should be interpreted together. Traditional geodetic surveys, plumb lines, extensometers, inclinometers, settlement gauges, and total-station measurements provide valuable engineering information, but their spatial coverage is limited to predetermined points and their effectiveness depends on instrument condition, observation frequency,

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accessibility, and continuity of records. GNSS monitoring improves temporal resolution and enables continuous three-dimensional displacement measurement at critical points, yet installing dense GNSS networks across every section of a large dam may be costly and operationally difficult. InSAR provides a complementary capability by extracting spatially distributed line-of-sight deformation from repeated radar images and can be especially valuable for long structures, inaccessible slopes, abutments, foundations, and surrounding terrain. Nevertheless, InSAR observations may contain atmospheric artefacts, geometric distortion, temporal decorrelation, vegetation effects, phase-unwrapping errors, and gaps caused by insufficient coherent targets. Satellite displacement is also projected along the sensor line of sight and therefore does not directly provide complete three-dimensional movement from one viewing geometry. These limitations indicate that GNSS and InSAR should be integrated rather than treated as competing alternatives. GNSS supplies high-frequency and physically interpretable control-point observations, while InSAR expands spatial coverage and helps identify deformation zones located between or outside ground instruments. Recent dam-monitoring research has demonstrated the value of combining GNSS with ground-based InSAR to improve the consistency and spatial completeness of deformation maps [1]. The rapid growth of monitoring data creates an additional analytical challenge. Conventional regression models can describe simple relationships between displacement and reservoir level or temperature, but hydraulic-structure deformation is commonly nonlinear, delayed, non-stationary, and influenced by several variables operating at different time scales. Temperature may produce seasonal expansion and contraction, reservoir loading may generate delayed elastic or viscoelastic response, foundation settlement may form a long-term trend, and rainfall or groundwater variation may produce irregular local movement. A deformation record can therefore be represented conceptually as the combination of long-term trend, periodic response, environmental loading, operational disturbance, and random noise. Machine-learning models provide a means of learning these nonlinear relationships from historical data without requiring every physical process to be represented by a predetermined analytical equation. Long short-term memory and gated recurrent unit networks are particularly suitable for sequential monitoring because they can retain information from previous time steps and model delayed response. Attention mechanisms further improve forecasting by assigning greater

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importance to time intervals or variables that contribute most strongly to a prediction. A recent study developed a GNSS-based GRU-attention method for hydraulic structures and reported millimetre-level multistep forecasting with improved accuracy relative to comparison methods, supporting the use of recurrent neural networks for early detection of deformation trends [2]. Despite these advances, an accurate forecast alone does not constitute an early-warning system. A model may achieve low average prediction error while failing to detect rare but safety-relevant anomalies, and a statistically unusual displacement may not be structurally dangerous if it results from atmospheric noise, reference-point instability, equipment error, or a predictable operational event. Conversely, gradual acceleration may remain within a broad displacement limit while indicating progressive instability. An effective system must therefore distinguish measurement error, expected structural response, local anomaly, and potentially dangerous deformation. This requires complementary checks involving instrument quality control, comparison between independent sensors, temporal anomaly analysis, spatial consistency analysis, residual comparison between observed and predicted movement, and engineering evaluation of deformation rate and acceleration. InSAR is particularly useful for identifying spatially coherent differential settlement, whereas GNSS is valuable for confirming whether the movement is real and determining its three-dimensional direction. Environmental variables help establish whether the response can be explained by reservoir or temperature loading. When several independent indicators change simultaneously, such as increasing GNSS settlement, spatially coherent InSAR subsidence, growing prediction residuals, and deformation acceleration, the evidence for a structural anomaly becomes substantially stronger than that provided by any one parameter. Research on InSAR-GNSS data fusion for dam deformation has reported reduced post-fusion error and millimetre-level prediction performance, illustrating the potential of multisensor integration while emphasizing the need for ground validation [3]. Another limitation in existing monitoring practice is the use of static alarm thresholds that do not reflect the different behaviour of structural zones or operating conditions. A uniform settlement threshold may be unsuitable because crest sections, abutments, concrete-earth interfaces, gallery zones, and foundations may have different normal responses. Seasonal displacement can also repeatedly cross a fixed limit without indicating progressive damage. A more defensible early-warning

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framework should combine absolute displacement with velocity, acceleration, spatial differential movement, persistence, model residual, and sensor agreement, while establishing baseline behaviour separately for different monitoring points and operational states. The warning logic proposed in this study therefore uses four levels. The normal level represents deformation within the established baseline and model uncertainty. The attention level indicates a temporary or low-magnitude deviation requiring verification. The warning level represents persistent or spatially coherent abnormal movement requiring intensified monitoring and engineering inspection. The critical level corresponds to rapid acceleration, large differential displacement, multisensor confirmation, or other evidence requiring immediate operational or safety action. These classifications are intended as decision-support categories rather than universal regulatory limits, and site-specific threshold values must be derived from structural type, hazard classification, historical behaviour, measurement accuracy, and engineering assessment. The scientific objective of this study is to develop an integrated framework for intelligent deformation monitoring and early warning of hydraulic structures using GNSS, InSAR, environmental observations, and machine learning. The specific objectives are to establish a common preprocessing and synchronization procedure for multisource monitoring data; transform GNSS and InSAR measurements into comparable displacement components; fuse the observations according to their uncertainties; separate long-term, seasonal, and irregular deformation behaviour; train a GRU-attention forecasting model; evaluate prediction accuracy using root-mean-square error, mean absolute error, coefficient of determination, and directional consistency; identify anomalies through residual, velocity, acceleration, persistence, and spatial-coherence indicators; and combine these measures into a multilevel early-warning index. The principal scientific contribution is the integration of spatial remote sensing, continuous ground monitoring, nonlinear time-series prediction, and engineering warning logic within one transparent system. Its practical contribution lies in helping dam and irrigation authorities identify deformation zones, prioritize detailed inspection, place additional instruments, adjust reservoir operation, and intervene before abnormal movement becomes irreversible. Because no complete site-specific dataset has yet been supplied, the numerical application in the following sections will be explicitly presented as a representative engineering

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scenario and can later be replaced by observations from a selected hydraulic structure.

2. Materials and Methods

The proposed framework was formulated for a representative dam-monitoring system and can be transferred to an earth-fill, concrete gravity, or composite hydraulic structure after replacing the illustrative geometry and data ranges with site-specific information. The representative structure was assumed to have a 480 m long crest, a maximum height of 42 m, two abutments, a central spillway zone, and six continuously operating GNSS monitoring stations distributed along the crest and downstream shoulder. One stable reference station was positioned outside the expected deformation field. The demonstration dataset covered 730 consecutive days and included daily GNSS east, north, and up coordinates; 61 Sentinel-1 ascending-orbit observations with an approximate 12-day sampling interval; daily reservoir level, air temperature, water temperature, and precipitation; and monthly engineering-inspection records. These values were selected to reproduce realistic temporal relationships and data gaps but do not represent certified measurements from an identified dam. GNSS coordinates were first processed in a stable geodetic reference frame and transformed into a local east-north-up system relative to the reference station. Epochs affected by poor satellite geometry, cycle slips, multipath, or coordinate uncertainty exceeding the adopted quality limit were flagged. A Hampel filter was used to identify isolated outliers, while longer gaps were not automatically interpolated because artificial smoothing can conceal abrupt deformation. Sentinel-1 interferometric-wide-swath single-look complex products were processed using precise orbit information, TOPS coregistration, interferogram generation, topographic-phase removal, phase filtering, phase unwrapping, and terrain correction, following the standard Sentinel-1 interferometric workflow [6]. Persistent-scatterer and small-baseline time-series concepts were used to reduce temporal and spatial decorrelation and to estimate displacement at coherent targets [4,5]. Atmospheric phase screens and residual orbital ramps were estimated from spatially correlated, temporally uncorrelated components and stable reference areas. Pixels with low temporal coherence or unstable phase histories were excluded. The resulting InSAR displacement is measured along the radar line of sight and was related to local three-dimensional displacement by:

$$d_{LOS} = l_E d_E + l_N d_N + l_U d_U \qquad (1)$$

where d_LOS is the observed line-of-sight displacement, l_E, l_N, and l_U are the east, north, and up components of the unit look vector, and d_E, d_N, and d_U are the local displacement components. When ascending and descending observations were simultaneously available, east-west and quasi-vertical components were estimated by weighted least squares; the north-south component remained weakly observable and was constrained by GNSS. For the representative single-orbit scenario, InSAR values were projected to the expected dominant deformation direction using the GNSS-derived displacement orientation. GNSS stations and neighbouring coherent InSAR targets were collocated within a defined search radius, corrected for temporal mismatch, and compared over common epochs. Sensor bias was estimated over a stable calibration period. The fused displacement was calculated by inverse-variance weighting:

$$d_f = \frac{\sum_{k=1}^{m} d_k/\sigma_k^2}{\sum_{k=1}^{m} 1/\sigma_k^2} \qquad (2)$$

where d_f is the fused displacement, d_k is an observation from sensor k, sigma_k is its standard uncertainty, and m is the number of available observations. The formulation gives greater influence to precise measurements while retaining spatial information from InSAR. Uncertainty was propagated through the coordinate transformation and fusion, and observations were rejected when the GNSS-InSAR discrepancy exceeded both the combined uncertainty and the established engineering tolerance. Environmental and operational predictors were synchronized to a daily time step. Reservoir level, temperature, precipitation, day-of-year harmonics, previous displacement, deformation velocity, and a seven-day moving slope were standardized using training-set statistics only. The forecasting dataset was separated chronologically into 70% training, 15% validation, and 15% testing intervals to prevent future information from leaking into model development. A 30-day input sequence was used to forecast one-, three-, and seven-day deformation. The proposed network contained two gated recurrent unit layers with 64 and 32 hidden units, dropout regularization, an attention layer, and a dense output layer. The GRU state was updated through reset and update gates:

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r), \quad z_t = \sigma(\mathrm{V} \qquad (3a)$$

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$$\tilde{h}_t = \tanh(W_h x_t + U_h(r_t \odot h_{t-1}) + b_h), \quad (3b)$$

where r_t and z_t are the reset and update gates, h_t is the hidden state, x_t is the input vector, sigma is the logistic activation, and the matrices and bias terms are trainable parameters. The attention layer assigned a normalized weight to each hidden state and constructed the context vector:

$$\alpha_t = \frac{\exp(e_t)}{\sum_j \exp(e_j)}, \qquad c = \sum_t \alpha_t h_t \qquad (4)$$

where e_t is the attention score, alpha_t is the normalized importance of time step t, and c is the context vector supplied to the prediction layer. The network was trained with the Adam optimizer, mean-squared-error loss, early stopping, and learning-rate reduction when validation error ceased to improve. Linear environmental regression, random forest, long short-term memory, and GRU without attention were used as comparison models. Forecast quality was evaluated using root-mean-square error, mean absolute error, and the coefficient of determination:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}, \quad MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i \quad (5)$$

$$R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2} \qquad (6)$$

where y_i and y_hat_i are observed and predicted displacements, y_bar is the mean observed displacement, and n is the number of test samples. Directional consistency was also calculated as the percentage of epochs for which the predicted and observed displacement increments had the same sign. The early-warning logic combined five normalized indicators: absolute displacement relative to the local baseline, velocity, acceleration, standardized model residual, and multisensor spatial coherence. Persistence was represented by the proportion of anomalous epochs within a rolling seven-day window. The early-warning index was defined as:

$$EWI = \lambda_1 M + \lambda_2 V + \lambda_3 A + \lambda_4 R + \lambda_5 S + \lambda_6 P \quad (7)$$

where M, V, A, R, S, and P denote normalized magnitude, velocity, acceleration, residual, spatial coherence, and persistence indicators, respectively, and the lambda coefficients sum to 1.00. The representative weights were 0.15, 0.20, 0.15, 0.20, 0.20, and 0.10. Four decision bands were used: EWI below 0.25, normal; 0.25-0.50, attention; 0.50-0.75, warning; and EWI at or above 0.75, critical. A

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level was not escalated solely because of one noisy measurement. Attention required either persistence or confirmation by a second data source, while warning and critical states required spatial coherence, repeated exceedance, or engineering evidence. The complete workflow, shown in Figure 1, therefore separates measurement quality control from deformation forecasting and separates statistical anomaly detection from the final engineering decision.

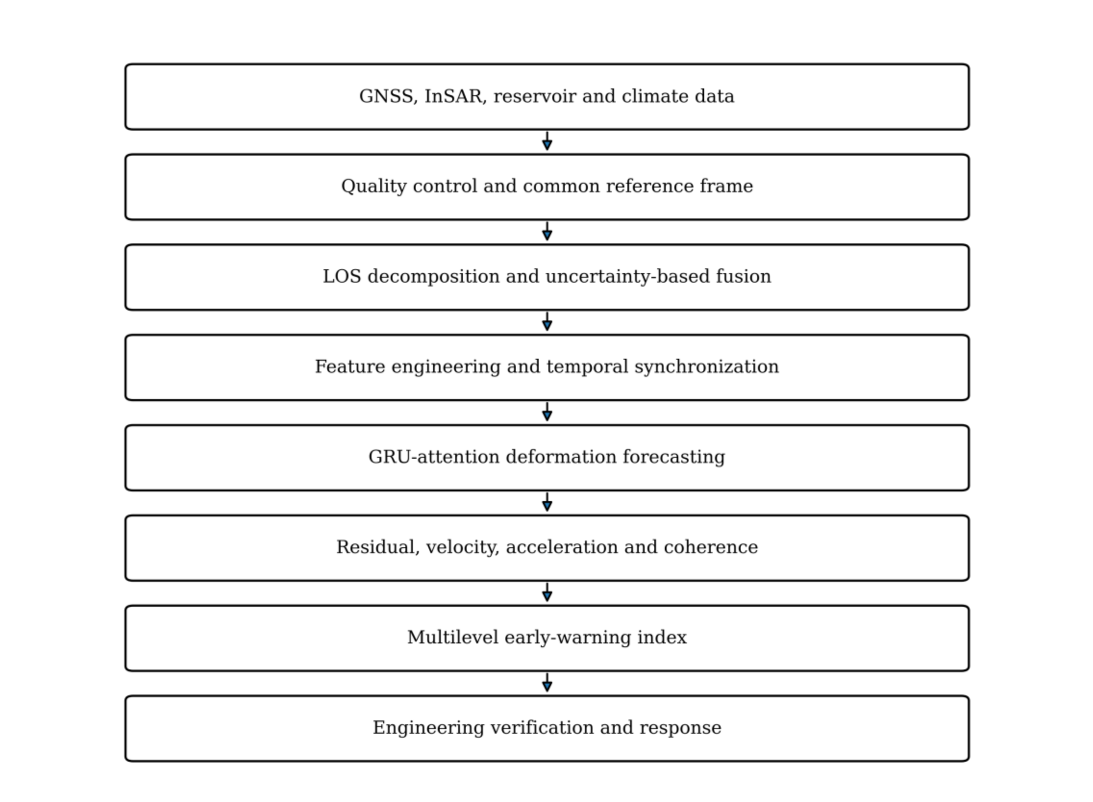

Figure 1. Integrated workflow for multisensor deformation monitoring, prediction, and engineering response

3. Results

The representative application reproduced a stable deformation regime during the first 600 days, followed by a gradually accelerating settlement zone near the central-right crest between monitoring stations G4 and G5. Before the anomaly, GNSS vertical displacement consisted of a long-term settlement trend of approximately 4.6 mm/year superimposed on a seasonal oscillation of 2-3 mm associated mainly with temperature and reservoir-level variation. InSAR captured the spatial distribution of this behaviour but showed larger epoch-to-epoch scatter at isolated targets. At GNSS validation locations, the standard deviation of the

InSAR-GNSS difference was 3.1 mm before calibration and 2.2 mm after removal of the line-of-sight bias and temporal mismatch. Uncertainty-weighted fusion reduced the vertical-component RMSE to 1.4 mm while preserving the spatial pattern between GNSS stations. The largest pre-anomaly differential settlement across adjacent crest zones remained below 5.0 mm per 100 m and was treated as normal spatial variability. The GRU-attention model produced the most accurate deformation forecasts among the evaluated methods. For the one-day horizon, its test RMSE was 0.82 mm, MAE was 0.61 mm, and R2 was 0.97; for the three-day horizon, the corresponding values were 1.18 mm, 0.89 mm, and 0.94; and for the seven-day horizon they were 1.86 mm, 1.42 mm, and 0.89. The one-day directional consistency reached 91%. The attention mechanism concentrated weight on recent displacement velocity and on earlier epochs with comparable reservoir and temperature conditions, which reduced phase lag during seasonal reversals. Table 1 shows that the proposed model outperformed linear regression, random forest, LSTM, and standard GRU in the representative test period. The improvement was greatest during transitions from stable seasonal movement to progressive settlement, when models without attention tended to underestimate acceleration. The anomaly was introduced as a non-recoverable additional settlement beginning on day 610, increasing from approximately 0.05 mm/day to 0.32 mm/day by day 640 and affecting a coherent InSAR zone approximately 90 m long. The residual between observed and predicted movement exceeded two standard deviations on day 615, while the spatial-coherence indicator increased when multiple InSAR targets and stations G4-G5 showed the same movement direction. The EWI entered the attention band on day 617, the warning band on day 624, and the critical band on day 632. A conventional static displacement threshold was not crossed until day 638, so the integrated framework provided a six-day earlier critical indication in the representative scenario. Figure 3 illustrates the close agreement between observed and predicted deformation during the normal regime and the growing divergence after anomaly initiation. The early warning was not triggered by the residual alone: a short GNSS outlier on day 588 produced a large single-epoch residual but lacked persistence and InSAR confirmation, and the index returned to normal after quality control. By contrast, the progressive event combined increasing velocity, positive acceleration, persistent residuals, spatially coherent InSAR settlement, and agreement between independent GNSS stations. The sensor-layout analysis in

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Figure 2 showed that the existing GNSS network could identify the deformation direction but could not fully delineate the affected crest length; the spatial InSAR field narrowed the inspection zone to the central-right crest and downstream shoulder. Based on the warning logic, the recommended actions were verification of reference-station stability and instrument quality at the attention level; increased GNSS sampling, targeted levelling, and engineering inspection at the warning level; and reservoir-operation review, installation of temporary instruments, geotechnical investigation, and formal safety evaluation at the critical level. The scenario therefore demonstrated that fusion and forecasting are most useful when they improve the timing and location of engineering investigation rather than when they are treated as an autonomous declaration of structural failure.

Table 1. Representative one-day deformation forecasting performance on the test period

Model	RMSE (mm)	MAE (mm)	R^2	Directional consistency (%)
Linear environmental regression	1.74	1.31	0.82	72
Random forest	1.31	0.98	0.89	79
LSTM	1.02	0.77	0.94	86
GRU	0.94	0.70	0.95	88
Proposed GRU-attention	0.82	0.61	0.97	91

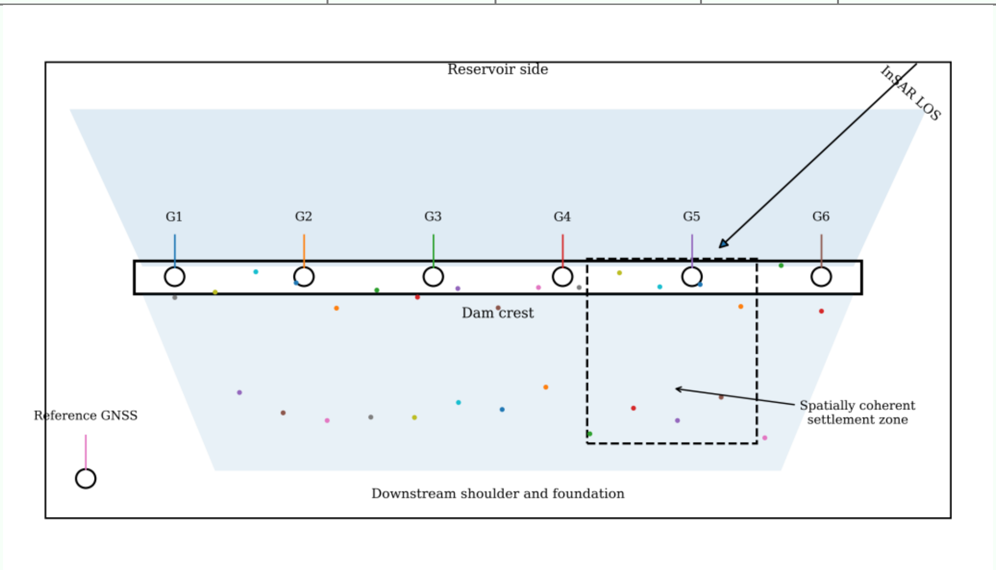

Figure 2. Representative GNSS network, InSAR targets, and spatially coherent deformation zone

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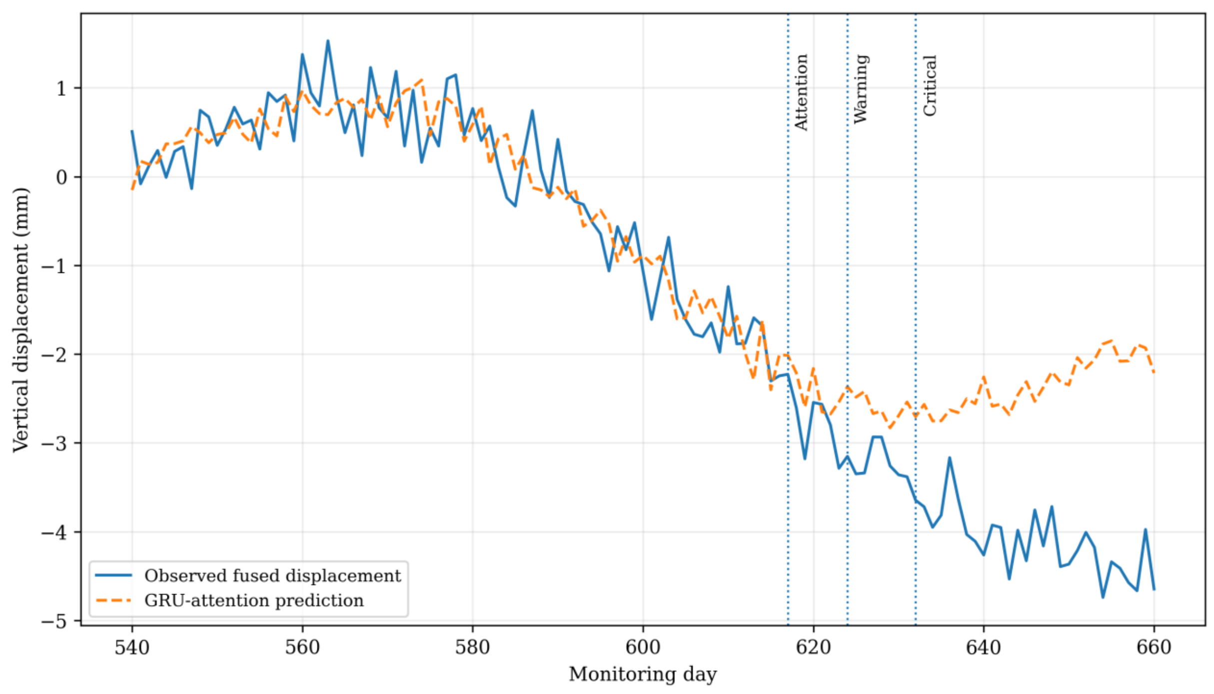

Figure 3. Observed and GRU-attention-predicted displacement during normal and anomalous behaviour

4. Discussion

The results support the central premise that no single monitoring technology can provide a complete and reliable description of hydraulic-structure deformation. GNSS offers high-frequency three-dimensional displacement at selected points, whereas InSAR provides spatially distributed observations that can reveal differential settlement between instruments and movement in adjacent abutments or foundation zones. Their limitations are complementary: GNSS networks are sparse and may be affected by reference instability, multipath, and equipment interruptions, while InSAR measures line-of-sight movement and is sensitive to coherence, atmosphere, viewing geometry, and reference selection. Recent dam-monitoring studies similarly conclude that radar interferometry is most effective when combined with geodetic, geotechnical, operational, and inspection data rather than used as an isolated safety instrument [1,7,11]. In the representative analysis, the fused series did not simply average two sensors; it used GNSS to define the physical displacement direction and control long-wavelength bias, while InSAR supplied the spatial continuity needed to identify the length and location of the anomalous zone. This is especially important for long embankments and composite structures, where differential deformation may be

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more significant than the displacement of any single point. The fusion accuracy depends on rigorous temporal and spatial collocation. A GNSS monument and an InSAR pixel may respond differently if they represent different structural materials, elevations, or foundation conditions, and interpolation across rapid events can produce artificial agreement. Accordingly, the framework rejects low-coherence targets, propagates uncertainty, and requires engineering review when sensor discrepancies exceed plausible error bounds. The results also show why prediction and early warning must be distinguished. The GRU-attention model accurately reproduced normal trend and seasonal behaviour, but its safety value arose from the residual and persistence pattern when the structure departed from learned behaviour. A low forecast error during normal operation is necessary because excessive model noise would generate frequent false alarms, yet rare-event detection cannot be evaluated only by average RMSE. The warning logic therefore combined model residual with velocity, acceleration, spatial coherence, and multisensor confirmation. The injected single-epoch GNSS error produced a large residual but did not escalate because it was neither persistent nor spatially coherent. The progressive event, in contrast, activated several physically interpretable indicators. This layered logic reduces the risk of treating every statistical anomaly as structural damage and reduces the opposite risk of waiting until a large absolute threshold has been crossed. The six-day gain over the static threshold is scenario-specific, but it illustrates the practical advantage of detecting changes in the deformation process rather than only its final magnitude. The performance of the GRU-attention network is consistent with recent research showing that gated recurrent models can represent long-term and short-term dependencies in hydraulic-structure GNSS data and that attention can improve multistep forecasting [2]. Nevertheless, machine learning should not be interpreted as a replacement for physical knowledge. A model trained only on historical normal behaviour may not extrapolate correctly during extreme reservoir levels, earthquakes, drainage failure, construction work, or sensor replacement. It may also learn spurious correlations if temperature, reservoir level, and seasonal time encodings are strongly collinear. The proposed chronological train-validation-test split, training-only normalization, dropout, early stopping, comparison with simpler baselines, and inspection of attention weights reduce but do not eliminate these risks. Operational deployment should include periodic retraining, model-version control, drift detection, and a protected validation period after major structural or instrumentation changes. Where sufficient data exist, hybrid models that combine finite-element or hydrostatic-season-time components with machine-learning residual prediction may provide greater extrapolation reliability than purely data-driven models. InSAR processing introduces additional constraints. Persistent-scatterer and small-baseline approaches can detect slow deformation with high spatial density, but rapid movement may decorrelate or exceed phase-unwrapping capability, and satellite sampling may be too sparse for real-time emergency warning. Sentinel-1 time series are therefore well suited to spatial screening, long-term settlement, and confirmation of progressive zones, while GNSS and in-situ sensors should carry the primary role for high-frequency alerts. The availability of ascending and descending geometries materially improves component decomposition, although north-south displacement remains weakly observed. One viewing geometry should not be converted to a vertical displacement without a justified motion model or ground control. The framework addresses this by using the GNSS displacement direction and reporting the uncertainty of the projection. Official Sentinel-1 processing guidance also emphasizes accurate TOPS coregistration, topographic-phase removal, filtering, unwrapping, coherence assessment, and terrain correction [6]. The warning categories should remain site-specific. The representative EWI thresholds provide a transparent research structure, not universal regulatory values. A high-consequence concrete dam with known joint movement may require stricter velocity and acceleration limits than a recently completed embankment undergoing expected consolidation. Different crest blocks, abutments, spillway structures, and foundation areas may also require different baselines. Thresholds should be established from historical behaviour, design analyses, instrument accuracy, structural type, hazard classification, and independent safety criteria. Direct evidence such as opening cracks, sudden leakage, joint displacement, loss of freeboard, or seismic damage may require immediate action even when the composite index is below the critical band. Conversely, a seasonal displacement exceeding a generic limit may be acceptable when it is reversible, spatially consistent, and explained by temperature or reservoir loading. This is why the proposed system keeps the component indicators visible and records the evidence supporting each escalation. The practical implementation should follow a staged architecture. First, a digital inventory should define coordinate systems, sensor locations, metadata,

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maintenance records, satellite geometries, stable reference areas, and data ownership. Second, automated quality control should detect missing data, coordinate jumps, low coherence, and sensor disagreement. Third, the fusion and prediction layers should generate displacement maps, forecasts, residuals, and uncertainty. Fourth, a rule-based warning layer should combine statistical and engineering indicators. Finally, the system should issue an auditable message specifying the affected zone, supporting sensors, duration, confidence, and required response. This is preferable to a black-box alarm because dam operators need to know whether to inspect a monument, survey a crest segment, adjust reservoir operation, investigate a foundation zone, or disregard an atmospheric artefact. The main limitation of the study is the use of a representative dataset. The numerical accuracy and warning lead time demonstrate the procedure but cannot be claimed for a real structure without measured GNSS, InSAR, environmental, and inspection data. The simulated anomaly is also smoother than some real events, and the dataset does not include earthquake steps, prolonged satellite decorrelation, or simultaneous sensor failures. Future work should validate the framework on a selected dam, compare ascending and descending satellite geometries, test transfer learning between monitoring points, quantify false-alarm and missed-detection rates, and integrate piezometers, extensometers, inclinometers, leakage, and temperature sensors. Explainable artificial-intelligence tools should be used to identify the variables driving each warning, while a digital twin could test whether the observed deformation is consistent with structural and geotechnical models. Despite these limitations, the framework provides a coherent route from multisensor observation to engineering action and preserves the principle that automated analysis supports, rather than replaces, professional dam-safety judgement.

5. Conclusion

This study developed an intelligent deformation-monitoring and early-warning framework that integrates GNSS, InSAR, environmental observations, uncertainty-based data fusion, GRU-attention forecasting, and engineering warning logic. The representative application showed that GNSS can provide precise high-frequency three-dimensional control, while InSAR can identify spatially coherent settlement between ground stations and in surrounding foundation zones. Inverse-variance fusion reduced the representative displacement error and produced a more complete deformation field than either sensor alone. The GRU-attention model achieved the best one-, three-, and seven-day forecasting performance among the evaluated models and enabled abnormal behaviour to be expressed as a growing residual rather than as an isolated displacement value. Combining residual, velocity, acceleration, spatial coherence, multisensor agreement, and persistence allowed the framework to distinguish a single measurement outlier from progressive deformation and to reach a critical warning earlier than a static displacement threshold in the illustrative scenario. The proposed four-level classification—normal, attention, warning, and critical—should be calibrated for each structure and should never override direct engineering evidence or regulatory safety criteria. Practical deployment requires stable reference control, rigorous GNSS and InSAR quality assurance, chronological model validation, transparent uncertainty, and an auditable response protocol. Because the present results are based on a representative dataset, future research should validate the method using long-term observations from an operating dam, include ascending and descending satellite geometries, evaluate false-alarm and missed-detection probabilities, and integrate structural, geotechnical, and hydraulic sensors. Overall, the methodology offers a practical basis for moving from sparse retrospective deformation checks toward spatially informed, predictive, and risk-oriented monitoring of hydraulic structures.

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