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Key Points:

- A semi-parametric forward model generates synthetic electrical resistivity and water storage data using stochastic water content fields
- Bayesian Evidential Learning (BEL) bypasses traditional inversion to estimate total water storage (TWS) with credible uncertainty intervals
- The refined BEL–Electrical Resistivity Tomography framework with stratified sampling and adaptive weighting provides uncertainty-aware estimates of TWS

Supporting Information:

Supporting Information may be found in the online version of this article.

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Quantifying Water Content of a Landfill With ERT Data by Bayesian Evidential Learning

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Abstract Accurate estimation of water storage in municipal solid waste landfills is critical for assessing leachate-generation risk yet remains challenging due to pronounced heterogeneity. Here we apply Bayesian Evidential Learning (BEL) to directly relate Electrical Resistivity Tomography (ERT) data to total water storage (TWS), bypassing explicit inversion. A semi-parametric forward model generates 100,000 synthetic TWS–ERT pairs spanning stochastic saturation fields and petrophysical uncertainty. A Bayesian neural network captures data-dependent predictive uncertainty, while stratified resampling and adaptive weighting mitigate class imbalance across the TWS range. The framework yields well-calibrated posterior estimates and consistent agreement with independent water-balance benchmarks from four field transects. The BEL–ERT workflow provides a rapid, open-source alternative for landfill monitoring and highlights the potential of uncertainty-aware learning from synthetic ensembles to quantify water storage in heterogeneous near-surface systems.

Plain Language Summary Managing landfill sites requires knowing how much water is stored within them, as it is the source of harmful leachate that contaminates groundwater. Traditional methods for estimating this water content often involve complex calculations that can be uncertain and hard to interpret. In our study, we introduce a new approach that combines electrical measurements taken on the landfill with advanced statistical techniques to directly estimate the total water storage. This method uses computer simulations to link the instruments' measurements and the actual water storage. The result is a reliable prediction of water storage, along with an estimate of the uncertainty in that prediction. This improved method can help landfill managers better assess environmental risks and make informed decisions to protect public health and the environment.

1. Introduction

Modern sanitary engineered landfills are an increasingly important component of waste management strategies in Europe, offering enhanced waste stabilization and energy recovery. However, their effective design, operation, and long-term aftercare are essential to minimize environmental pollution, particularly the risk of groundwater contamination. A critical aspect of landfill management is the prediction of leachate transport within the waste body, which depends heavily on accurately estimating water storage capacity. Water storage influences both leachate generation and contaminant transport, making it a key factor in environmental risk assessment. To address this, researchers have developed a range of numerical models that simulate moisture flow and solute transport in landfill environments (Li et al., 2021; Lu et al., 2019). Among these models, dynamic water storage within the waste matrix has emerged as a key parameter for evaluating environmental risks and optimizing waste treatment efficiency.

In previous work, we employed a Travel-Time-Distribution (TTD) model combined with data assimilation techniques to estimate water storage within the landfill (Heimovaara & Wang, 2025; Wang & Heimovaara, 2025b). By conceptualizing water storage as a zero-dimensional state, representing bulk storage without accounting for spatial variability, we avoided the complexities associated with spatially distributed modeling. However, this approach relied exclusively on indirect observations of leachate outflow, making the accuracy of the storage estimates highly dependent on the model's structural assumptions and parameterization. To reduce uncertainty and enhance the robustness of these estimates, we integrate independent, direct measurements of water storage into the modeling framework.

Hydrogeophysical methods have become essential tools for characterizing subsurface hydraulic properties in complex environments such as landfills. Among these, Electrical Resistivity Tomography (ERT) is particularly

valuable due to its capacity to infer water content by measuring subsurface electrical resistivity, which correlates with water saturation through Archie's Law. ERT has been widely applied in landfill settings to detect water content and monitor the spatial distribution of leachate and gas (Feng et al., 2017; Zhan et al., 2019). For instance, Zhan et al. (2019) demonstrated the use of ERT to delineate leachate distribution within a controlled landfill cell, while Hu et al. (2019) successfully applied time-lapse ERT surveys to monitor landfill dewatering. These studies highlight ERT's potential as a non-invasive, spatially resolved method for tracking hydrological processes within waste bodies.

Another approach involves hydrogeophysical coupled inversion, in which water content and related parameters (e.g., hydraulic and petrophysical properties) are estimated directly from ERT measurement data, bypassing the explicit inversion of electrical resistivity (Linde & Doetsch, 2016). This method integrates ERT data into a coupled hydrogeophysical model and uses petrophysical relationships, such as Archie's Law, to link resistivity with water content. By circumventing the traditional resistivity inversion step, coupled inversion can mitigate the effects of regularization, reduce uncertainty arising from inversion artifacts, and improve the accuracy of water content estimates. However, its implementation in practice is challenging because it requires a well-constrained flow model, and in landfill settings, the problem is exacerbated by highly heterogeneous water distributions that cannot be parameterized by a small set of explicit variables.

Since our objective is to estimate the total water storage (TWS) within the waste body, rather than its spatial distribution, bypassing the ill-posed inversion process allows for a more direct and robust estimation. To achieve this, we introduce a novel approach based on the Bayesian Evidential Learning (BEL) framework (Scheidt et al., 2018), which estimates landfill water storage from ERT measurement data without performing conventional inversion. BEL employs a forward model to generate prior samples of both the target variable (water storage) and the observable variable (ERT signals), enabling the statistical learning of their relationship (Thibaut et al., 2021). Unlike traditional inversion techniques, BEL avoids the challenges associated with ill-posedness and regularization artifacts by focusing on learning from ensembles of model realizations. The BEL framework has demonstrated effectiveness across various applications, including seismic data interpretation (Pradhan & Mukerji, 2020), geophysical parameter estimation (Ahmed et al., 2024; Hermans et al., 2016, 2018), and experimental design optimization (Thibaut, 2023; Thibaut et al., 2021, 2022). A Python toolbox is also available for implementing BEL (Thibaut, 2025).

In this study, we apply the BEL framework to landfill water storage estimation by developing a semi-parametric forward model that simulates ERT signals as a function of water storage. The key novelty is that we bypass any explicit flow model, instead generating stochastic water-content distributions. This allows BEL to be applied in settings where physically based flow models are difficult to define or constrain, thereby broadening its range of applications. A neural network is then trained to learn a direct statistical mapping between the simulated ERT data and TWS, thereby bypassing the traditional inversion process. This approach provides a robust alternative for estimating water storage, reducing uncertainties associated with model structural assumptions, ill-posed inversion artifacts, and measurement noise.

2. Methods

2.1. Bayesian Evidential Learning

The general objective of data-driven estimation is to obtain the posterior distribution of the target property $p(\mathbf{h}|\mathbf{d}_{\text{obs}})$, where $\mathbf{h}$ represents the target variable (e.g., water content) and $\mathbf{d}_{\text{obs}}$ represents the available observations (e.g., ERT data). In traditional model-driven approaches, the measured data $\mathbf{d}_{\text{obs}}$ are used to optimize the model parameters $\mathbf{m}$, which include inversion parameters that need to be fixed or optimized and subsurface properties used in the forward model. Once the model is optimized, it predicts the target variable $\mathbf{h}$. In the context of ERT data analysis, this process involves using $\mathbf{d}_{\text{obs}}$ to estimate a resistivity map $\mathbf{m}$ of the subsurface. A key limitation of this approach is the dimensionality mismatch: the number of unknown model parameters n_m is typically much larger than the number of available observations n_d , making the inversion process ill-posed. In addition, traditional deterministic inversion often ignores uncertainty, while fully stochastic approaches such as Monte Carlo inversion are computationally expensive.

The BEL framework reorganizes this relationship differently by avoiding direct optimization of model parameters. Instead, prior distributions of the model parameters $\mathbf{m}$ are first defined based on available knowledge. The

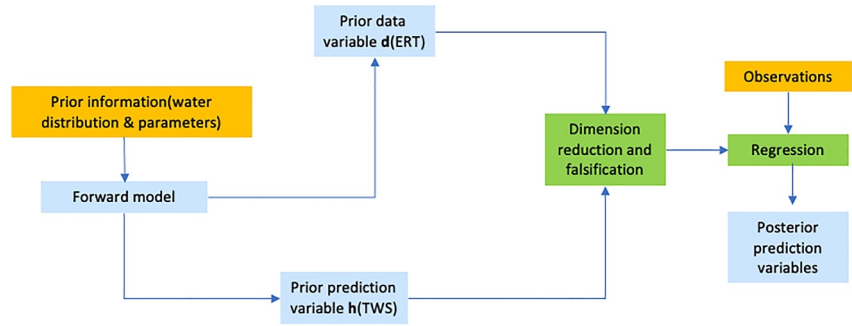


Figure 1. Diagram for Bayesian Evidential Learning method in this study.

target variable $\mathbf{h}$ is computed using a forward model $\mathbf{h} = f_1(\mathbf{m})$, while the observable variable $\mathbf{d}$ is generated using another forward model $\mathbf{d} = f_2(\mathbf{m})$. This approach enables BEL to learn a direct statistical relationship between the observations $\mathbf{d}$ and the target variable $\mathbf{h}$ without explicitly solving an inverse problem, thereby bypassing the need for resistivity inversion. Crucially, BEL does not remove uncertainty but explicitly propagates prior variability through the workflow, resulting in uncertainty-aware predictions.

A diagram showing the conceptual differences between the traditional method and the BEL framework can be found in Figure S1 in Supporting Information S1. Figure 1 provides an overview of the BEL method as applied in this study, including the generation of prior samples, forward modeling of both observable and target variables, and the statistical learning process. In the following sections, we describe these components in detail.

2.2. Forward Model

Given the high spatial heterogeneity of water distribution in landfills, we approximate the three-dimensional waste body with a two-dimensional cross-section water distribution map. This simplification enables the use of a 2D mesh composed of rectangular grid cells. To further reduce model complexity, we assume hydrostatic conditions within the waste body. Under this assumption, the volumetric water content can be determined if the positions of saturated zones are known. The volumetric water content in the landfill cover layer is represented by the variable θ_{cl} .

To simulate the presence of saturated zones within the waste body, we developed a stochastic procedure that randomly assigns saturated cells within the 2D mesh. Each cell is treated as a binary variable—either saturated or unsaturated. The generation process begins by sampling a fraction value k , which defines the proportion of saturated cells relative to the total number of cells. This value is drawn from a uniform distribution, $k \sim U(0.01, 0.7)$, with bounds selected based on the minimum and maximum water level measurements observed in the field.

Once the saturated cells are defined, the volumetric water content θ for each grid cell is calculated on a column-wise basis using the water retention curve described by Equations 1 and 2.

$$S_{\text{eff}} = \begin{cases} 1 & \text{if } h_w \geq 0 \\ (1 + (\alpha|h_w|)^n)^{-m} & \text{if } h_w < 0 \end{cases} \quad (1)$$

where S_{eff} is the effective saturation, h_w is the pressure head, which is positive below, negative above the water table, α is the inverse of the air entry suction (units: L^{-1}), θ_r is the residual water content, θ_s is the saturated water content, θ is the volumetric water content, and n and $m = 1 - 1/n$ are empirical water retention parameters.

The volumetric water content θ is computed as:

$$\theta = \theta_r + S_{\text{eff}}(\theta_s - \theta_r) \quad (2)$$

In cases where a column contains no saturated cells, we assume the water table is just below the column due to the presence of a drainage layer. When multiple saturated cells occur in a column, each disconnected saturated region

is treated as a localized bottom boundary condition for the unsaturated cells positioned above it. This approach enables a more realistic representation of heterogeneous saturation patterns within the landfill.

The TWS is computed by summing the volumetric water content across all grid cells within the waste body. Because the top cover layer is composed of soil, a separate set of Archie's Law parameters is used to account for its distinct hydrogeophysical properties. The height of the cover layer is set equal to the height of the first layer in the computational mesh. As a simplification, the water retention curve is not applied within the cover layer. Instead, each cell in this layer is assigned a uniform volumetric water content, denoted as θ_{cl} . During the sample generation process, θ_{cl} is randomly sampled from a uniform distribution, with its lower and upper bounds derived from the cover layer saturation estimates $\mathbf{v}_{cl}$ presented in Heimovaara and Wang (2025). Because ERT measurements are most sensitive to resistivity changes near the surface, our choice of a spatially constant θ_{cl} effectively treats the entire cover as a single “effective soil” whose moisture state controls the shallow resistivity response. Sampling θ_{cl} from a narrow prior (based on model estimation obtained from Heimovaara and Wang (2025)) ensures that the cover-layer sensitivity is realistic, so that the BEL model can focus on learning the deeper relationship between resistivity and water storage in the waste body. At this stage, the forward model $f_1(\cdot)$ for computing TWS is fully defined.

Following the water storage calculation, the electrical resistivity of each cell is determined using Archie's Law, as described in Equation 3.

$$\rho = a_{arc} \rho_w \phi^{-m_{arc}} S_{eff}^{-n_{arc}} \quad (3)$$

where ρ is bulk resistivity of the waste, a_{arc} is tortuosity factor, ρ_w is resistivity of the leachate, ϕ is porosity, m_{arc} is cementation exponent, S_{eff} is water saturation, n_{arc} is saturation exponent. In this work, the petrophysical and hydraulic parameters ($a_{arc}, m_{arc}, n_{arc}, \phi, \rho_w$) are assumed as spatially uniform but uncertain effective values at the ERT support scale; they are sampled from broad prior ranges and their variability is propagated through the BEL workflow. The field experiment employs both Dipole–Dipole (DD) and Schlumberger (SLM) protocols to obtain apparent resistivity data. The corresponding observable ERT signals are then simulated using a numerical simulator implemented in PyGIMLi (Rücker et al., 2017). This process defines our model to data $f_2(\cdot)$.

2.3. Priors and Prior Falsification

The BEL framework aims to directly learn the relationship between observations and target variables by performing statistical regression between $\mathbf{h}$ (e.g., water storage) and $\mathbf{d}_{obs}$ (e.g., ERT measurements). Training such a model requires a sufficiently large data set of paired samples ($\mathbf{h}, \mathbf{d}_{obs}$).

In most real-world applications, however, only a single set of observations $\mathbf{d}_{obs}$ is available, and the corresponding target variable $\mathbf{h}$ is either unknown or cannot be measured directly. This lack of labeled data renders direct regression based solely on field data impractical. To overcome this, we generate synthetic training samples using the forward models $f_1(\cdot)$ and $f_2(\cdot)$, enabling the construction of a representative statistical relationship between observations and the target variable.

In the standard BEL approach, training samples are generated by running forward simulations $f_1(\mathbf{m})$ and $f_2(\mathbf{m})$ using prior distributions of model parameters $\mathbf{m}$. These prior distributions are typically informed by laboratory and field studies reported in previous research (Saneiyan et al., 2024; Zeng et al., 2017; Zhang et al., 2021).

Most previous applications have relied on geostatistical realizations to generate random subsurface fields, which are then used in flow simulations. The advantage of our approach is that it bypasses this step by directly sampling water-content distributions, so that no permeability field is required. This greatly reduces computational cost by eliminating the need for a numerical flow model. The potential drawback is that the resulting distributions may be physically unrealistic or overly simplistic. The approach remains valid, however, if the generated realizations adequately span the range of possible true distributions. It is important to note that building a statistical regression model from a finite training set requires caution, as there is no guarantee that the resulting predictions will be statistically or physically feasible. In a Bayesian framework, the posterior distribution must lie within the support of the prior (Hou & Rubin, 2005; Scheidt et al., 2018). To safeguard validity, it is therefore essential to verify that the observed measurement data are consistent with both the assumed priors and the outputs of the forward models.

This verification step, known as *falsification*, is performed in BEL before any regression or prediction step (Fang et al., 2022; Hermans et al., 2018; Michel et al., 2020; Pradhan & Mukerji, 2020). It involves comparing the predicted data $\mathbf{d}$, generated via forward modeling, with the observed data $\mathbf{d}_{\text{obs}}$. In low-dimensional cases, this comparison can often be made visually. However, due to the high dimensionality of the ERT data in this study, we first apply a dimensionality reduction technique. The resulting lower-dimensional representation is then used in a classification-based falsification method to assess whether the observed data are statistically consistent with the prior samples. We employ Principal Component Analysis (PCA) in the dimensionality reduction step to explain approximately 99% of the total variance in the data set.

Assuming that all generated samples of $\mathbf{d}$ are drawn from a common underlying distribution, the observed measurement $\mathbf{d}_{\text{obs}}$ is expected to belong to the same distribution. If it is classified as an outlier, the prior is considered falsified. We perform this classification using a one-class Support Vector Machine (SVM) (Bounsiar & Madden, 2014). The parameter $\nu = 0.05$ is chosen to allow up to 5% of synthetic samples to be treated as potential outliers, forming a robust boundary around the dominant structure of the prior distribution.

The prior distributions of the model parameters are iteratively adjusted until the observed measurements are identified as inliers. This ensures that the prior adequately spans the region of observation space where plausible system states exist.

2.4. Regression With a Neural Network

After performing dimension reduction and falsification, we can model the statistical relationship between the dimension-reduced target variable $\mathbf{h}^*$ and the observed data $\mathbf{d}^*$. Since dimension reduction was not performed on the target variable in our case, $\mathbf{h}^*$ is equivalent to $\mathbf{h}$. We used a deep learning method, specifically a Bayesian Neural Network (BNN) with Monte Carlo Dropout, to model this relationship and estimate prediction uncertainty.

The input data were standardized and transformed using PCA, retaining 99% of the variance. The data set was then divided into training (70%), validation (15%), and test (15%) subsets. Prior to training, we applied a stratified resampling scheme to mitigate class imbalance, ensuring that rare high- and low-TWS samples were adequately represented. This resampling strategy divides the TWS range into discrete bins and adaptively oversamples extreme bins by up to 1.8 $\times$, preserving both low- and high-end variability while avoiding redundancy in the mid-range. The initial and resampled TWS distributions are shown in Figure S4 in Supporting Information S1.

The BNN adopts a multi-head architecture that jointly predicts the mean (μ), data-dependent variance (σ^2), and predictive quantiles (q_{10} and q_{90}). The probabilistic formulation of the last layer allows for explicit modeling of epistemic uncertainty through a Bayesian linear layer with Gaussian priors ($\mu = 0$, $\sigma = 0.2$). The preceding layers are deterministic and consist of three fully connected layers with 128, 96, and 64 neurons, respectively, each followed by ReLU activation and light dropout (0.05–0.03). This “last-layer Bayesian” configuration effectively balances computational efficiency and uncertainty expressiveness.

Training uses a composite principled loss comprising four components: (a) a Gaussian negative log-likelihood that incorporates adaptive weighting for extreme samples, where high- and very-high-TWS observations receive larger weights based on their relative scarcity; (b) a Kullback–Leibler (KL) divergence term for Bayesian regularization with a gradually annealed coefficient (2×10^{-5} base weight); (c) quantile (pinball) losses for the q_{10} and q_{90} heads to learn the lower and upper quantile boundaries of the predictive distribution; and (d) a focal loss term to emphasize hard-to-predict examples. These components are combined with annealing schedules and adaptive coefficients to ensure stable convergence while preserving tail performance. The model is trained using the Adam optimizer (learning rate 5×10^{-5} , weight decay 1×10^{-5}) with early stopping and adaptive learning-rate scheduling.

To assess the adequacy of the training data size, we conducted a sample-size sensitivity analysis using ensembles of 5, 10, 20, 50, and 100 k realizations. The mean squared error (MSE) of the BNN predictions decreased consistently with increasing sample size but reached a plateau beyond 50 k samples. This indicates that around 50 k realizations are sufficient to capture the main variability in the ERT–TWS relationship. Nevertheless, we employed 100 k samples in the final model to ensure better representation of rare high- and low-TWS cases and to obtain smoother posterior statistics. The corresponding MSE convergence curve is shown in Supporting Information S1 (Figure S5 in Supporting Information S1).

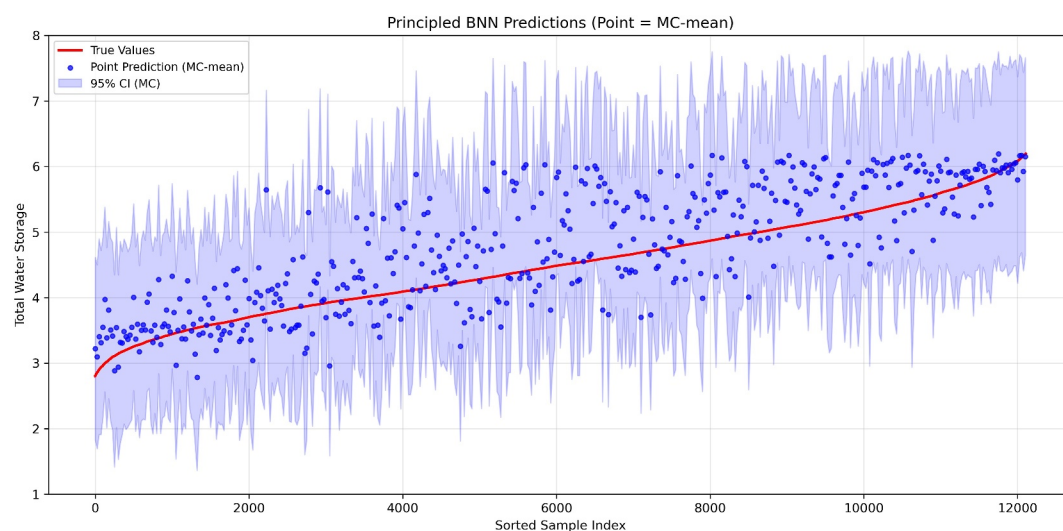


Figure 2. Bayesian neural network predictions with uncertainty on the test data set. The red curve shows the ground truth total water storage, sorted in ascending order. The blue points represent the mean prediction from 1,000 Monte Carlo samples and the shaded area indicates the 95% confidence interval.

During inference, 1000 stochastic forward passes are performed to generate the posterior predictive distribution. Each pass samples from the Bayesian weight posterior and the learned data-dependent variance σ^2 , while keeping the input data fixed. The predictive mean represents the expected TWS estimate, and the corresponding variance quantifies the overall predictive uncertainty. This formulation jointly captures epistemic uncertainty through weight sampling and aleatoric uncertainty through the learned σ^2 , enabling calibrated and noise-aware predictions across the full TWS range.

3. Results and Discussion

3.1. Falsification

The final prior ranges used to generate the synthetic training set are listed in Table S1 in Supporting Information S1. Figure S6 in Supporting Information S1 shows boxplots of the first five principal components (PCs) from the synthetic ensemble, with field observations overlaid as distinct markers. The observed samples align closely with the interquartile range (IQR) of the training distribution across all PCs, with none falling beyond the whiskers (5th–95th percentile), indicating that the field data are statistically consistent with the simulated data set. This supports the validity of the forward model used to generate the training data.

3.2. Regression and Prediction

The BNN was trained for 1,000 epochs with an early stop setting. Both training and validation losses converged smoothly without signs of overfitting (The loss curves are shown in Figure S7 in Supporting Information S1).

Figure 2 shows the BNN's predictive performance on held-out test samples. The predictive mean aligns closely with the true TWS (reported as equivalent water-column height in meters (m)) values, and the 95% credible intervals capture most of the ground-truth variability across the full range. Overall, the model provides well-calibrated and noise-aware predictions of TWS, effectively representing the nonlinear relationship between ERT data and subsurface moisture content.

Although the prior parameters were uniformly sampled, nonlinear transformations in the petrophysical and hydraulic relationships yield an approximately Gaussian TWS distribution, leading to underrepresentation of high-TWS cases. Stratified resampling combined with adaptive loss weighting was applied to restore balance at the distribution tails, improving predictive accuracy for extreme values while slightly increasing dispersion in the mid-range (Figure 2). This behavior reflects the expected trade-off between tail fidelity and central calibration.

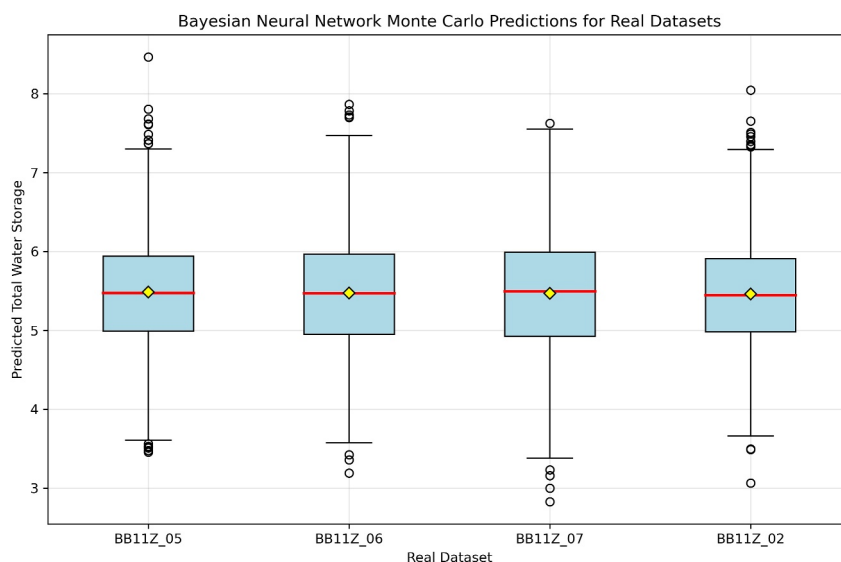


Figure 3. Boxplot of the Bayesian neural network's Monte Carlo predictions for the four real data sets (BB11Z_05, BB11Z_06, BB11Z_07, and BB11Z_02). Each box extends from the first quartile ($Q1$) to the third quartile ($Q3$), with the red horizontal line indicating the median. The whiskers represent a conventional range of $\pm 1.5 \times \text{IQR}$ from the quartiles, and any samples outside this range are shown as circular outliers. The yellow diamond within each box denotes the mean of the distribution. The light blue shading of the boxes helps visualize the spread and central tendency of the Monte Carlo predictions.

A test experiment with fixed physical parameters shows very accurate predictions with lower uncertainty (shown in Figure S8 in Supporting Information S1), highlighting the need for tighter constraints on key subsurface parameters. Parameter non-uniqueness is a well-recognized issue in hydrogeophysical inversion, as different combinations of subsurface properties (e.g., porosity, saturation, tortuosity) can yield similar resistivity responses (Linde & Doetsch, 2016; Tso et al., 2019). The fixed-parameter experiment confirms that reducing epistemic variability in the petrophysical parameters notably improves predictive stability and calibration, consistent with previous findings by Ahmed et al. (2024). We also did a simple test, using the traditional inversion method to calculate the TWS with a known petrophysical parameter set. The results are presented in Figure S9 in Supporting Information S1, where a significant bias is observed.

While our main focus has been on TWS, we also explored using ERT data to predict global water content histograms as an additional way to capture volumetric variability in a tractable form. Using 10 equally spaced bins over the 0–1 saturation range, we obtained illustrative results (Figure S10 in Supporting Information S1) that show the possibility of extending BEL–ERT toward predicting distributional characteristics of water content. This exploratory analysis highlights a promising direction for future work to more fully exploit the distributed sensitivity of ERT.

Figure 3 presents boxplots of the BNN's predictive distributions for four field data sets (BB11Z_05, BB11Z_06, BB11Z_07, and BB11Z02), where the trailing numbers indicate the measurement month. Each data set exhibits a spread of Monte Carlo predictions between approximately 3.5 and 7.5 m^3/m^2 , with the mean (yellow diamond) generally near 5.5 m^3/m^2 . This value is consistent with an independent water-balance estimate for the same landfill cell, which yields 4.6–6.0 m^3/m^2 (based on a releasable water content of 2.5–3.2 m^3/m^2 (Heimovaara & Wang, 2025), a residual volumetric water content of 0.15–0.2, and a recorded waste body height of 14 m). This comparison is approximate, since the residual water content may be lower in situ, and isolated perched water may be present. Nevertheless, the close agreement between the BEL–ERT predictions and the hydraulic model provides indirect support for the emulator's absolute scale, despite the absence of direct ground truth.

These results demonstrate that ERT data, interpreted through the BEL framework, can meaningfully quantify uncertainty in TWS. However, the ability to resolve changes in storage over time remains limited by the large predictive uncertainty arising from poorly constrained model parameters.

4. Conclusions

We present a BEL workflow that converts surface ERT measurement data into bulk water-storage estimates (TWS) for municipal solid waste landfills, bypassing the ill-posed resistivity inversion that traditionally limits hydrogeophysical applications.

The synthetic training ensemble, built from stochastic saturation fields and broad petrophysical priors, fully brackets the field ERT responses; one-class SVM falsification confirms that the retained realizations capture site variability. A last-layer BNN provides accurate and well-calibrated predictions across the full TWS range, with 95% credible intervals achieving near-nominal coverage. The results demonstrate that the framework effectively handles data noise and parameter variability while maintaining physical consistency between resistivity and water storage.

These findings establish BEL–ERT as a rapid, non-invasive tool for landfill water content monitoring, delivering uncertainty-aware estimates without inversion artifacts. Future work should integrate temporal monitoring and multi-method geophysical data sets to further constrain uncertainty. Beyond landfill applications, this approach offers a transferable framework for quantifying subsurface water storage in other highly heterogeneous near-surface systems.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

All data and scripts used in this paper are available at Wang and Heimovaara (2025a), <https://data.4tu.nl/datasets/3d08ee40-04f3-4b8f-94c1-018090ad2a09/2>.

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