Local refinement of a national-scale groundwater model

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Abstract

This method article presents a local refinement framework for a national-scale, machine learning-based groundwater model that predicts typical summer and winter water table depth at 10 × 10 m resolution at national scale of Denmark. While the existing baseline model provides high-resolution national coverage and is suitable for screening purposes, its accuracy remains insufficient for local groundwater management applications. The proposed method integrates new groundwater observations into the existing training dataset and retrains the baseline model to enhance local fidelity while preserving large-scale consistency. The approach is demonstrated for a 212 km² case study area using 100 synthetic groundwater observations. Cross-validation results show consistent improvements in mean error, mean absolute error, and root mean squared error compared to the baseline model, particularly when increased weights are assigned to new observations. The refined models produce improved precision in areas with new observations while maintaining baseline behaviour elsewhere, demonstrating its suitability for combining national datasets with local monitoring networks for improved decision support in climate adaptation, nature conservation and other applications.

Introduction

This method builds upon the national-scale machine learning-based groundwater model developed by Koch et al. (2021), which predicts typical summer and winter water table depth at 10 × 10 m resolution across Denmark. The model targets the uppermost groundwater table and generates high-resolution map products that are distributed through the Hydrological Information and Prognosis system (HIP, https://hipdata.dk/). The 10 m maps provide a valuable screening resource for Danish municipalities, water utilities and other decision makers for planning climate adaptation measures, particularly in relation to flood risk. The datasets are for example highlighted in the EPA's climate adaptation implementation (Danish EPA, 2025). Despite the high spatial resolution and overall improved precision compared to the process-based national hydrological model of Denmark (DK-model, Henriksen et al. (2022)), which operates at 100 m resolution, the 10 m models still lack sufficient accuracy to support local groundwater management decisions. Examples include expanding drainage capacities in urban areas or nature restoration planning involving groundwater-surface water interactions. The mean absolute error of the 10 m national baseline model is approximately 1 m, which may limit its applicability for local decision-making.

With increasing awareness of shallow groundwater challenges concerning flood resilience, irrigation planning, and nature conservation, together with the availability of cost-effective groundwater monitoring systems, many decision makers have invested in local groundwater monitoring networks. However, the integration of these point observations into spatial groundwater modelling workflows remains challenging and requires specialised technical expertise. The presented method aims to address this gap by equipping decision makers with a practical workflow for incorporating local groundwater observations into a state-of-the-art machine learning modelling framework. The method enables the generation of high-resolution maps of groundwater dynamics by combining national-scale databases with locally collected groundwater observations through machine learning models.

Resources required

The required resources are as follows:

- Sufficient computing environment (~25 Gigabyte RAM, not GPU dependent).
- Python 3.12 including the following packages, numpy, pandas, pyarrow, lightgbm, scikit-learn, gdal, geopandas, pyproj, shapely and fiona. Required versions are further specified in the environment.yml file available via Koch (2026b).
- Input data for machine learning model, *df_predcit.parquet* is available via Koch (2026a) and *df_train.parquet* is available via Koch (2026b).
- Auxiliary data and code provided by Koch (2026a, 2026b).
- Local groundwater observations representing typical winter and summer conditions.

Methodological protocols

Curating groundwater observations

New groundwater observations are the core input driving the local model refinement. The method requires a CSV file containing ETRS89 / UTM 32N coordinates (EPSG: 25832) together

with median summer and winter water table depths. Users are responsible for curating these medians given uncertainties in the underlying data, including short time series and well screen placement, as the model assumes that the well screen represents the uppermost groundwater table. Shallow wells can be identified through a combination of depth criteria-based lithology and the homogeneity of the lithostratigraphy of the well. The training data for the baseline model contains observations from the period 1991 to 2025. Both summer and winter groundwater levels must be provided. If only one seasonal estimate is available, users are encouraged to estimate the seasonal amplitude to derive the missing season. Summer medians should represent June to August, whereas winter medians should represent December to February. Further details regarding preprocessing are provided by Koch et al. (2021). The training data used to build the national baseline model are provided (df_train.parquet), and users are encouraged to explore which groundwater observations are already included in the national dataset using the available coordinates or the provided shapefile of the training data location and metadata. To demonstrate the method, 100 synthetic summer and winter observations were generated and are provided in Koch et al. (2021).

Retraining machine learning model

The local refinement is performed by retraining the underlying machine learning model. First, covariate data are extracted for the newly provided groundwater observations. The computational efficiency of this step depends on the size of the user-defined prediction domain. The model incorporates 22 covariates, which are specified by Koch et al. (2021) and Troldborg at al. (2026). After extraction, the covariate data are concatenated with the existing training dataset (df_train.parquet). Subsequently, the summer and winter models, including their associated uncertainty models (q10 and q90), are retrained using the predefined hyperparameters. Existing training observations may also be removed if they are considered unreliable or uncertain by the user. This can be done by dropping specific rows from the training dataframe. We advise users to explorer the training data through the provided shapefile where the wells can be linked to the the training dataframe using the WELLID column.

The newly added observations can be assigned additional influence during model training in two different ways, which can be controlled by parameters “weight_local” and “repeat_local” in the main script (main.py). The motivation is to force the machine learning model towards improved local accuracy while still retaining the large-scale relationships learned from the national dataset. The first option is data augmentation, where local observations are duplicated multiple times in the training dataset. The second option is weight assignment, where local observations are assigned higher weights in the loss function. By default, synthetic observations are assigned a weight of 1, while groundwater wells are assigned a weight of 2. Additional details are provided in Koch et al. (2021). The sensitivity of the two parameters will depend on the size of the new groundwater observations and how they agree with the baseline training data and therefore we encourage users to explore the sensitivity from case to case.

Model validation and prediction

In the provided scripts, the local refinement is evaluated using 4-fold cross-validation. Validation focuses specifically on the newly provided groundwater observations. First, a baseline model is

trained exclusively on the pre-existing national-scale training data, excluding the new observations. Subsequently, four refined models are trained including the new observations. The cross-validation scheme ensures that, for each model, 25% of the new observations are used for testing while 75% are used for training. In this way, each local observation is used exactly once for validation. By default, mean error (ME), mean absolute error (MAE), and root mean squared error (RMSE) are calculated and their mean value is calculated across the four validation folds. Validation is carried out separately for the summer and winter models.

In total, six models are trained, each generating 10 × 10 m water table depth maps. Predictions are produced for the local prediction domain specified by the user. Hyperparameters remain fixed during refinement, ensuring that model improvements are driven solely by the inclusion of the new groundwater observations. The outputs include predictions of typical summer and winter water table depth, together with two uncertainty bounds for each model: the 10th percentile (q10), representing the shallow bound, and the 90th percentile (q90), representing the deep bound. Together, these approximate an 80% confidence interval. All prediction maps are exported as GeoTIFF files and represent water table depth in cm below ground level.

Auxiliary outputs

In addition to the six prediction maps, several auxiliary outputs are generated. The 22 covariate raster layers are clipped to the local prediction domain and exported as GeoTIFFs. Furthermore, the training data are exported as a point shapefile covering the prediction domain. User-provided groundwater observations are labelled with "user" in the attributes TYPE and WELLID.

Demonstration

Validation on synthetic data

The presented method is demonstrated for an area surrounding the city of Sunds in Jutland with a simulation domain of approximately 212 km². A total of 100 synthetic groundwater observations were generated. Figure 1a illustrates the baseline training labels representing the national-scale training dataset also used in HIP. This dataset includes both in situ groundwater observations and synthetic labels representing expert-generated groundwater conditions along rivers, groundwater-connected lakes, and coastline. In addition, the 100 local observations used for refinement are shown in Figure 1b. Spatial clustering and comparable groundwater depth values are evident, reflecting the characteristics typically found in real-world monitoring datasets.

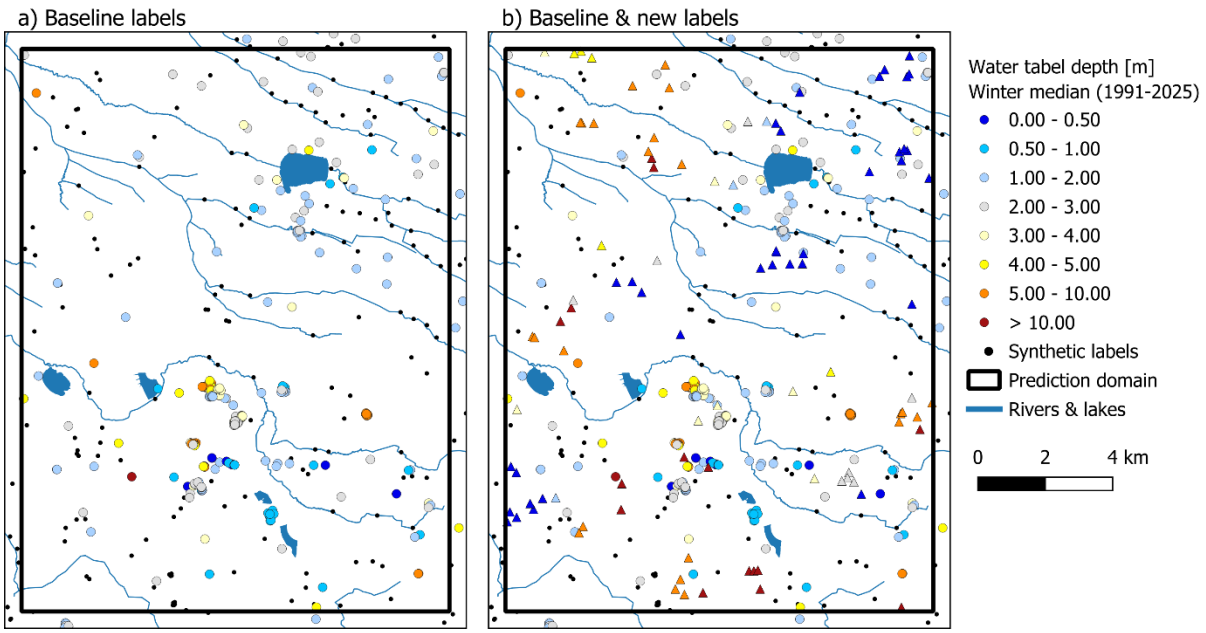

Figure 1. Observations of water table depth under typical winter conditions used as training labels for a) the national-scale baseline model shown as circles and b) the local model refinement shown as triangles. The training dataset also includes synthetic labels representing rivers and lakes.

Results from the 4-fold cross-validation using the 100 synthetic groundwater observations are presented in Table 1. Compared with the national-scale baseline model, all three performance metrics indicate improved model performance following local refinement. For both MAE and RMSE, model precision further improved when increasing the weight assigned to the new groundwater observations from 2 to 5 during training. This indicates that stronger weighting of local observations can enhance local model performance. It should be noted that the validation labels are synthetic, and therefore the practical implications of the reported performance metrics should not be overinterpreted. Nevertheless, the relative differences between the evaluated modelling scenarios clearly demonstrate the usability and functionality of the presented method.

Tabel 1. 4-fold cross-validation of the 100 synthetic groundwater observations (Figure 1b). Mean error (ME), mean absolute error (MAE), and root mean squared error (RMSE) for summer (s) and winter (w) groundwater predictions from the national-scale baseline model and two locally refined models. The local refinements were performed using two different weighting parameters (w) for the newly added groundwater observations.

	Baseline		**Local refinement (w=2)**		**Local refinement (w=5)**	
	s	**w**	**s**	**w**	**s**	**w**
ME [m]	**-0.86**	**-1.08**	**-0.62**	**-0.77**	**-0.66**	**-0.77**
MAE [m]	**3.64**	**3.96**	**2.88**	**2.91**	**2.73**	**2.76**
RMSE [m]	**4.34**	**4.79**	**3.56**	**3.64**	**3.44**	**3.54**

The resulting maps of typical winter conditions for the baseline model and the locally refined model are presented in Figure 2. The local refinement differs from the baseline model in accordance with the synthetic groundwater observations added during training. For example, a

cluster of deep groundwater observations has a pronounced influence in the north-western part of the prediction domain, resulting in deeper predicted groundwater levels. Similarly, the shallow groundwater observations introduced in the north-eastern part of the domain lead to overall wetter predicted conditions. It is also noteworthy that areas without additional observations, or areas where the added observations are consistent with the baseline model, remain largely unchanged after local refinement. This indicates that the refinement primarily affects locations supported by new observations while preserving the large-scale spatial patterns of the baseline model.

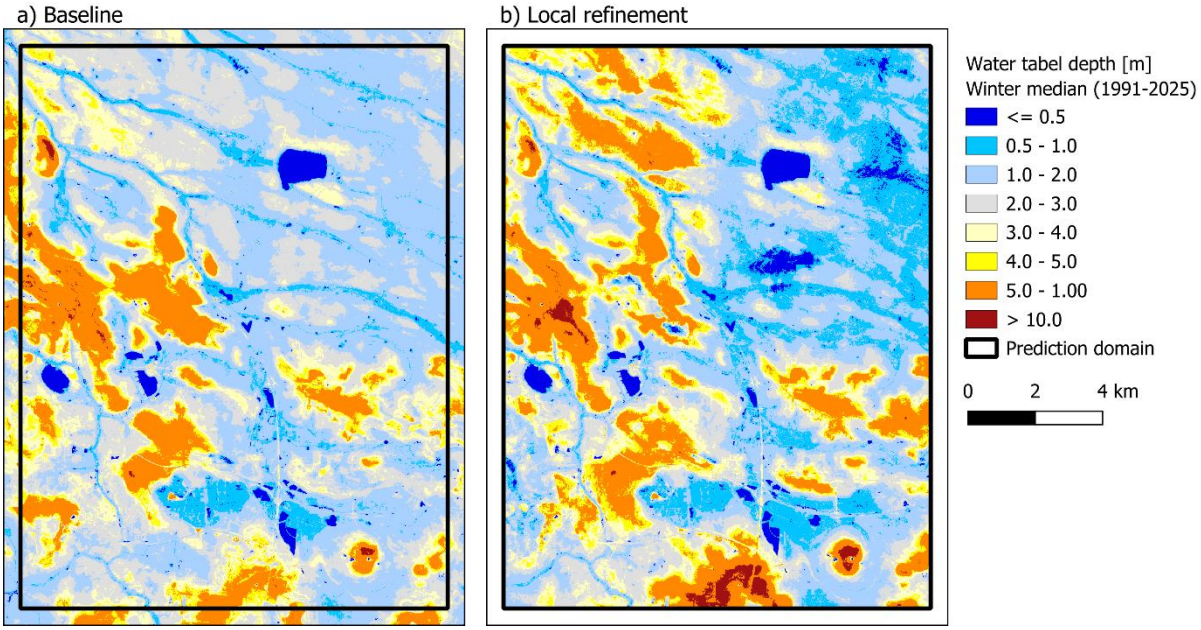

Figure 2. a) The baseline model derived from the existing national-scale training dataset, identical to the data distributed via HIP (https://hipdata.dk/). (b) The local refinement obtained from a retrained model incorporating 100 new groundwater observations (Figure 1b). Both maps represent typical winter groundwater conditions for the period 1991-2025.

This is further exemplified in Figure 3, where the differences between the baseline model and the refined model are shown. The spatial patterns of positive and negative differences in Figure 3a correspond well with the distribution of newly added deep and shallow observations, respectively, as illustrated in Figure 1b. Uncertainties, expressed as the width of the confidence interval (q90 - q10), are compared between the baseline and refined models in Figure 3b. Uncertainties are generally higher in areas where the refined model predicts a deeper groundwater table, whereas lower uncertainties are associated with areas with shallower groundwater conditions in the refined model. This indicates that uncertainty scales with groundwater depth; however, further investigations using real observations are required to draw robust conclusions. Theoretically, a higher density and improved quality of local observations should lead to an overall reduction in uncertainty.

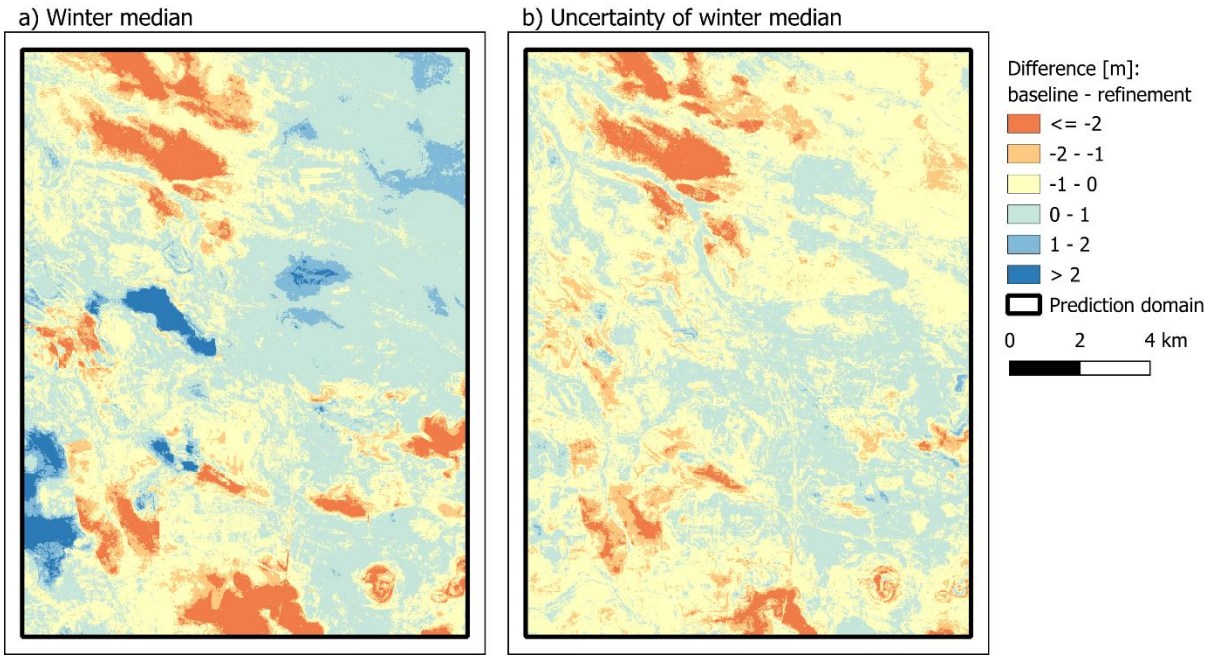

Figure 3. a) Spatial distribution of differences between the baseline model and the locally refined model (baseline - local refinement). b) Comparison of uncertainty between the baseline and refined model, expressed as the width of the 80% confidence interval (q90–q10).

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References

Danish EPA. (2025). Tillæg til spildevandsvejledningen: Kommunernes planlægning for terrænnært grundvand. Vejledning, nr. 83. Miljøstyrelsen. https://www2.mst.dk/Udgiv/publikationer/2025/12/978-87-7564-074-4.pdf

Henriksen, H. J., Schneider, R., Koch, J., Ondracek, M., Troldborg, L., Seidenfaden, I. K., ... & Stisen, S. (2022). A new digital twin for climate change adaptation, water management, and disaster risk reduction (HIP digital twin). Water, 15(1), 25.

Koch, J., Gotfredsen, J., Schneider, R., Troldborg, L., Stisen, S., & Henriksen, H. J. (2021). High resolution water table modeling of the shallow groundwater using a knowledge-guided gradient boosting decision tree model. Frontiers in Water, 3, 701726.

Koch, J. (2026a). Dataframe for 10 m water table depth predictions at DK-scale [Data set]. GEUS Dataverse. https://doi.org/10.22008/FK2/DUU3WM

Koch, J. (2026b). RefineWTD10m [Source code]. GEUS GitLab. Retrieved May 19, 2026, from https://geusgitlab.geus.dk/hydrology-public/RefineWTD10m

Troldborg, L., Ondracek, M., Koch, J., Schneider, R. J. M., Henriksen, H. J., Kragh, S. J., Gotfredsen, J., van Til, M., Jakobsen, A., Rasmussen, P., Pasten-Zapata, E., & Stisen, S. (2026).

203 Dokumentationsrapport vedr. modelleverancer til Hydrologisk Informations- og Prognosesystem
204 – Version 2 (GEUS Rapport 2026/9). De Nationale Geologiske Undersøgelser for Danmark og
205 Grønland. https://doi.org/10.22008/gpub/38964