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Is inversion based high resolution characterization of spatially heterogeneous river bed hydraulic conductivity needed and possible?

W. Kurtz¹, H.-J. Hendricks Franssen¹, P. Brunner², and H. Vereecken¹

¹Forschungszentrum Jülich GmbH, Institute of Bio- and Geosiences: Agrosphere (IBG-3), 52425 Jülich, Germany

²University of Neuchâtel, Centre for Hydrogeology and Geothermics, 2000 Neuchâtel, Switzerland

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Correspondence to: W. Kurtz (w.kurtz@fz-juelich.de)

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Abstract

River-aquifer exchange fluxes influence local and regional water balances and affect groundwater and river water guality and guantity. Unfortunately, river-aguifer exchange fluxes tend to be strongly spatially variable and it is an open research question to which degree river bed heterogeneity has to be represented in a model in order to achieve re-5 liable estimates of river-aquifer exchange fluxes. This research question is addressed in this paper with help of synthetic simulation experiments, which mimic the Limmat aquifer in Zurich (Switzerland), where river-aquifer exchange fluxes and groundwater management activities play an important role. The solution of the unsaturatedsaturated subsurface hydrological flow problem including river-aguifer interaction is 10 calculated for ten different synthetic realities where the strongly heterogeneous river bed hydraulic conductivities (L) are perfectly known. Hydraulic head data (100 in the default scenario) are sampled from the synthetic realities. In subsequent data assimilation experiments, where L is unknown now, the hydraulic head data are used as conditioning information, with help of the Ensemble Kalman Filter (EnKF). For each of 15

- the ten synthetic realities, four different ensembles of L are tested in the experiments with EnKF; one ensemble estimates high resolution L-fields with different L values for each element, and the other three ensembles estimate effective L values for 5, 3 or 2 zones. The calibration of higher resolution L-fields (i.e., fully heterogeneous or 5 zones)
- ²⁰ gives better results than the calibration of *L* for only 3 or 2 zones in terms of reproduction of states, stream-aquifer exchange fluxes and parameters. Effective *L* for a limited number of zones cannot always reproduce the true states and fluxes well and results in biased estimates of net exchange fluxes between aquifer and stream. Also in case only 10 head data are used for conditioning, the high resolution *L*-fields outperform the oth-
- ers. In case of less heterogeneous river bed hydraulic conductivities, a high-resolution characterization of L is less important. We conclude that for strongly heterogeneous river beds the commonly applied simplified representation of the streambed, with spatially homogeneous parameters or constant parameters for a few zones, might yield





significant biases in the characterization of the water balance. For strongly heterogeneous river beds, we suggest to adopt a stochastic field approach to model the spatially heterogeneous river beds geostatistically. The paper illustrates that EnKF is able to calibrate such heterogeneous streambeds on the basis of hydraulic head measurements, outperforming classical approaches.

1 Introduction

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It is now well known that rivers and streams closely interact with the adjacent groundwater body (Bouwer and Maddock, 1997; Winter, 1999; Sophocleous, 2002). These interactions have a number of consequences on the hydrological, chemical and biological environment around streams. For example, the resulting exchange fluxes between these two compartments influence the regional water balance and groundwater flow (Woessner, 2000) and thus also affect the yield of management activities close to streams, such as river bank filtration (Zhang et al., 2011; Schubert, 2002). Additionally, the different chemical composition of river water and groundwater also has implications on chemical and ecological processes around streams (Brunke and Gonser, 1997; Sophocleous, 2002).

The mechanisms of exchange between river systems and aquifers are complex and mainly depend on the pressure difference between stream and aquifer (Sophocleous, 2002), the form of the river bed (Cardenas et al., 2004; Boano et al., 2006), hydraulic properties of the river bed and the adjacent aquifer (Genereux et al., 2008) and the state of hydraulic connection between river and groundwater (Brunner et al., 2009). Exchange fluxes can exhibit a high degree of spatial and temporal variability which is often related to the spatial heterogeneity of hydraulic parameters of the river bed and the adjacent aquifer (Conant, 2004; Rosenberry and Pitlick, 2009; Genereux et al., 2008) what makes the model-based prediction of exchange fluxes challenging. Calver

(2001) compared literature data on river bed permeabilities which ranged from 10^{-9} to $10^{-2} \,\text{ms}^{-1}$ with a concentration of values in the range of 10^{-7} to $10^{-3} \,\text{ms}^{-1}$. A striking





feature in this data compilation is that estimated river bed permeabilities can also vary considerably for a single measurement site. This variability of hydraulic river bed properties can be found at different scales along a river reach. Genereux et al. (2008) determined river bed conductivities with permeameter tests for 46 locations of a 262 m long

- river reach. They observed a spatial variation in hydraulic conductivity of nearly four orders of magnitude ranging from approximately 1 × 10⁻⁷ to 7.5 × 10⁻⁴ m s⁻¹. They also found that measured river bed conductivities had a bimodal distribution and tended to be higher in the middle of the stream. Hatch et al. (2010) estimated river bed conductivities along a 11 km long river reach of Pajaro River and determined values ranging from 10⁻⁶ to 10⁻⁴ m s⁻¹. Springer et al. (1999) determined hydraulic conductivities for
- five reattachment bars of Colorado river over a range of 200 miles. Measured hydraulic conductivities varied over 2 orders of magnitude within the reattachment bars and differences between the medians of the five reattachment bars were up to one log unit.

Different modelling studies have already tried to assess the consequences of river

- ¹⁵ bed and aquifer heterogeneity on the prediction of exchange fluxes between streams and groundwater. For example, Bruen and Osman (2004) investigated the impact of heterogeneous aquifer hydraulic conductivities on river-aquifer exchange fluxes with a synthetic 2-D stream-aquifer model. They compared Monte Carlo simulations using heterogeneous fields of hydraulic conductivity with simulations using homogeneous
- fields. This comparison was made for different geostatistical parameters and connection regimes between river and aquifer. They found that the uncertainty in fluxes increases with an increasing degree of heterogeneity. They also found that a homogeneous model of hydraulic conductivities gave similar results as their Monte Carlo simulations under connected conditions whereas it gave different predictions when river
- and aquifer were disconnected and unsaturated conditions were present below the river bed. Fleckenstein et al. (2006) compared simulation results for six realisations of geostatistically simulated facies distributions with a homogeneous aquifer model and found comparable net seepage fluxes for the different models. However, they also identified that the different facies distributions show considerable variability in the





spatial distribution of seepage fluxes and in the state of connection between stream and aquifer. Kalbus et al. (2009) investigated the effect of heterogeneous conductivities within the streambed and the adjacent aquifer by simulating 2-D groundwater and heat transport using the leakage concept. They found that the heterogeneity of aquifer

- ⁵ properties has more impact on river-aquifer exchange than the one of the streambed. However, they also mention that homogeneous streambeds lead to an unrealistic homogenisation of water fluxes between river and aquifer. Frei et al. (2009) simulated the spatio-temporal distribution of seepage fluxes for a losing river reach in a Monte Carlo framework. They applied a hydrofacies model for the distribution of hydraulic conduc-
- tivities and found that highly permeable parts of the river reach (≈ 50 % of total length) make up 98 % of total seepage within their simulations. They argue that heterogeneity at the hydrofacies scale dominates the spatial pattern of river-aquifer interactions and that within-facies heterogeneity is of minor importance.

These different studies emphasize that the incorporation of heterogeneity in models for river-aquifer exchange can be important for a reliable prediction of exchange fluxes. In practical applications river bed conductivities are mostly estimated through calibration but heterogeneity is often neglected in the calibration procedure. One reason is that measurements of river bed conductivities are usually scarce and an estimation of the corresponding heterogeneity would require intensive field measurements. Espe-

- cially for larger streams in-situ measurements are difficult to perform because of the higher discharge. As a consequence, in most cases there is only limited prior knowledge on the heterogeneity of hydraulic parameters for a certain site. Another reason is that the computational demand for inversions with gradient-based methods and also the complexity of the inversion increases with a higher resolution representation of
- heterogeneity in the model. Due to a lack of prior knowledge on the magnitude and variability of river bed properties and in order to ease the inversion procedure, leakage parameters are often lumped together in leakage zones, i.e., the inversion is only done for very few parts of the river and the underlying heterogeneity is reduced to the different leakage zones. Irvine et al. (2012) carried out a systematic analysis on





the simplification of heterogeneity to quantify its implications on the prediction of infiltration fluxes. They simulated infiltration curves (i.e., the relationship between water table depth and infiltration flux) for a variety of heterogeneous distributions of river bed conductivities. Different data points from these synthetic infiltration curves were then

- ⁵ used to calibrate models with a homogeneous distribution of river bed conductivities. Forward simulations with the derived homogeneous values of river bed conductivities were subsequently used to compare the simulated infiltration curves with the equivalent ones for the fully heterogeneous medium. They found that the calibrated homogeneous models reproduced exchange fluxes well when the state of connection between stream
- and aquifer was equal for calibration and prediction of the homogeneous models. However, when the state of connection was transitional or differed between calibration and prediction, the homogeneous models could not adequately reproduce the infiltration fluxes of the corresponding heterogeneous references.

One way to account for the underlying heterogeneity of river-aquifer systems in the calibration of groundwater models in a stochastic framework is the Ensemble Kalman Filter (EnKF) (Evensen, 1994). EnKF and its variants have already been applied successfully for the characterization of heterogeneous subsurface properties in groundwater modelling. Examples are the work of Chen and Zhang (2006); Hendricks Franssen and Kinzelbach (2008); Nowak (2009) who assimilated piezometric heads with EnKF

- to improve the estimation of hydraulic conductivity fields. Sun et al. (2009) assessed the value of different deterministic ensemble filters for subsurface characterization. Liu et al. (2008) and Li et al. (2012) used tracer data to infer hydraulic conductivity (and porosity) fields. The studies of Jafarpour and Tarrahi (2011) and Huber et al. (2011) addressed the influence of variogram uncertainty and prior information in the initial pa-
- rameter ensemble on the estimation of hydraulic conductivity fields with EnKF. Zhou et al. (2011) and Schoeniger et al. (2012) investigated techniques to account for non-Gaussianity in the assimilation with EnKF and Camporese et al. (2009) jointly assimilated piezometric heads and discharge data for subsurface characterization. A general advantage of ensemble based data assimilation with EnKF and its variants is that they



are able to calibrate model parameters on the basis of the forward integration of an ensemble of different parameter fields and therefore explicitly account for the high variability of hydraulic parameters in natural settings. Therefore, this methodology should also be well suited for the characterization of highly variable river bed properties. In

- ⁵ Kurtz et al. (2012) EnKF has been applied specifically to river-aquifer systems in order to identify the temporal change of river bed conductivities. In this study we concentrate on the question whether the estimation of a few effective values for river bed hydraulic conductivity can reproduce spatially and temporally strongly variable river-aquifer exchange fluxes with the use of data assimilation. For this purpose we compare different ensembles of leakage parameters that either resemble the fully heterogeneous struc-
- ture of different synthetic reference fields or where three different degrees of spatial aggregation are used. Our specific research questions are:
 - To what degree does a zonation of river bed properties change predicted exchange fluxes between river and aquifer compared to a full representation of river bed heterogeneity?
 - Is EnKF able to identify the main structural features of a fully heterogeneous field of river bed conductivities through assimilation of hydraulic head measurements?
 - How does EnKF perform for different parameterization approaches (i.e., detailed representation of heterogeneity versus few zones) under conditions with different amounts of observation data?

2 Data assimilation with the Ensemble Kalman Filter

2.1 General description of the data assimilation algorithm

The Ensemble Kalman Filter (EnKF) is a sequential data assimilation approach which can be utilized to improve the prediction capability of a particular model in a Monte





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 Carlo framework. The methodology was originally applied for atmospheric and oceanographic models (e.g., Evensen, 1994; Houtekamer and Mitchell, 1998) and later used in modified variants, which include parameter estimation in surface hydrology (e.g., Moradkhani et al., 2005) and subsurface hydrology (e.g., Chen and Zhang, 2006; Liu
 ⁵ et al., 2008; Hendricks Franssen and Kinzelbach, 2008; Nowak, 2009). The basic idea of EnKF is that different model realizations (e.g., with different forcings and/or parameters) are propagated forward in time until state measurements become available. The predicted states are then improved by optimally combining the ensemble of model predictions and measurement data where measurement errors and the uncertainty of

¹⁰ model predictions are optimally weighted. EnKF can also be used to jointly estimate model states and parameters. In this case the model states ψ_i and the model parameters ϕ_i for realization *i* are combined in the state-parameter vector Ψ_i (e.g., Chen and Zhang, 2006; Hendricks Franssen and Kinzelbach, 2008):

$$\mathbf{\Psi}_i = \begin{pmatrix} \boldsymbol{\psi}_i \\ \boldsymbol{\phi}_i \end{pmatrix}$$

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¹⁵ For each assimilation cycle (i.e., at times when measurements become available) EnKF then performs a Bayesian update on the ensemble of the state-parameter vector Ψ .

$$\rho(\mathbf{\Psi} \mid \mathbf{y}^0) \propto \rho(\mathbf{y}^0 \mid \mathbf{\Psi}) \rho(\mathbf{\Psi})$$

where $p(\Psi | y^0)$ is the posterior (updated) distribution of the state-parameter vector Ψ given the observations y^0 , $p(y^0 | \Psi)$ is the likelihood of measurements y^0 given Ψ and $p(\Psi)$ is the prior distribution of Ψ . The prior of the states ψ (as part of Ψ) is usually obtained by advancing each realization *i* of the ensemble with a model *M*:

$$\boldsymbol{\psi}_{i}^{t} = M\left(\boldsymbol{\psi}_{i}^{t-1}, \boldsymbol{\phi}_{i}, \boldsymbol{\zeta}_{i}\right)$$
(3)

where $\boldsymbol{\psi}_{i}^{t}$ is the predicted state vector for time step t, $\boldsymbol{\psi}_{i}^{t-1}$ is the predicted state vector of the preceding time step t - 1, $\boldsymbol{\phi}_{i}$ are model parameters and $\boldsymbol{\zeta}_{i}$ are model forcings.



(1)

(2)

The posterior distribution of Ψ in Eq. (2) is then calculated with the EnKF analysis scheme which proceeds in the following steps: First, the forecasted values of ψ at observation points have to be extracted from the ensemble:

 $\hat{\boldsymbol{\psi}}_{i}^{t}=\boldsymbol{\mathsf{H}}\boldsymbol{\psi}_{i}^{t}$

⁵ where $\hat{\psi}_{i}^{t}$ is the state vector at observation points and **H** is a matrix that maps or interpolates the whole state vector ψ_{i}^{t} on the observation points. Next, the measured states y^{0} have to be perturbed with values from a normal distribution for each realization. This perturbation is necessary for an optimal functioning of the data assimilation algorithm (Burgers et al., 1998) and the variance of this perturbation is usually derived from the measurement error of the state measurement:

$$\boldsymbol{y}_i = \boldsymbol{y}^0 + \boldsymbol{\varepsilon}_i$$

where y_i are the perturbed observations for realization *i*, e_i is the corresponding perturbation vector and y^0 is the measurement vector.

Finally, the posterior distribution of Ψ is found by applying the following equation on each ensemble member *i*:

$$\mathbf{\Psi}_{i}^{a} = \mathbf{\Psi}_{i}^{t} + \alpha \mathbf{G} \left(\mathbf{y}_{i} - \mathbf{H} \mathbf{\Psi}_{i}^{t} \right)$$
(6)

where Ψ_i^a is the analysed (updated) state-parameter vector for realization *i*, Ψ_i^t is the forecasted state-parameter vector (with ψ_i^t from Eq. 3) and y_i is the perturbed measurement vector. α is a damping factor which is used to decrease the effect of filter inbreeding for parameter updates (see Hendricks Franssen and Kinzelbach, 2008). **G** is the Kalman gain which is calculated as follows:

 $\mathbf{G} = \mathbf{C}\mathbf{H}^T(\mathbf{H}\mathbf{C}\mathbf{H}^T + \mathbf{R})^{-1}$

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where **C** is the covariance matrix of Ψ^t and **R** is the covariance matrix of observation data y^0 . The Kalman gain **G** is calculated once for all ensemble members and weights



(4)

(5)

(7)

the uncertainties in the prediction of Ψ from the forward simulations with the measurement error of y^0 . In the analysis step (Eq. 6) the weighted factors of **G** are used to correct each member of Ψ_i^t with the residuals at observation points (bracketed term in Eq. 6). In order to derive **G** not the full covariance matrix of Ψ^t has to be calculated but it is sufficient to only calculate the covariances between Ψ^t and $\hat{\psi}^t$:

$$\mathbf{C}\mathbf{H}^{\mathcal{T}} = \begin{pmatrix} \mathbf{C}_{\boldsymbol{\psi}^{\mathsf{t}}\hat{\boldsymbol{\psi}}^{\mathsf{t}}} \\ \mathbf{C}_{\boldsymbol{\phi}\hat{\boldsymbol{\psi}}^{\mathsf{t}}} \end{pmatrix}$$

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2.2 Specific usage of EnKF for river-aquifer interactions

In this study the focus is on the investigation of river-aquifer exchange fluxes. Thus the model states of interest are piezometric heads h and the most relevant model paramters are hydraulic conductivities of the river bed which are implemented in the model as leakage coefficients L. Therefore, the state-parameter vector Ψ which was introduced in the previous section is composed of h and $\log(L)$. The model $M(\psi_i^{t-1}, \phi_i, \zeta_i)$ that is used to advance h in time is a groundwater model that is capable of simulating variably saturated flow and that includes a parameterization to simulate river-aquifer the covariance matrix \mathbf{R} includes the measurement errors of observation data on the diagonal but covariances between observation points are assumed to be zero (i.e., measurement errors are assumed to be independent).

3 Model description

Synthetic data assimilation experiments were performed with a 3-D finite element model of the Limmat valley aquifer in Zurich (Switzerland). The boundary conditions for this model are given schematically in Fig. 1. Groundwater recharge is imposed as a flux boundary condition on the first model layer. Groundwater inflows from the surrounding hills on the northern and southern boundary of the model were also treated

(8)



as flux boundary conditions. Within the model domain also management activities take place: groundwater is withdrawn close to the river through several bank filtration and drinking water wells. The pumped water from the bank filtration wells is recharged to the aquifer through several recharge wells and three recharge basins which are located

south of the drinking water wells. At the western side of the model domain a constant head boundary condition is imposed. The two rivers in the model (Limmat and Sihl) reside at the northern and eastern boundary of the model respectively and river stages are imposed on each river node of the model.

All model forcings (recharge, lateral inflows, river stages, pumping rates) are transient and based on real-world measurements for that site. A more detailed description on the calculation of forcing data is given in Hendricks Franssen et al. (2011). Fig. 2 gives an overview on the forcing data used for the numerical experiments.

The groundwater modelling software SPRING (Delta h Ingenieurgesellschaft mbH, 2006) was used to numerically solve the variably saturated flow equation for this model for each time step and each realization of the parameter ensembles. In SPRING, riveraquifer exchange fluxes for each leakage node *i* are calculated according to a Cauchy-type boundary condition (leakage principle):

$$Q_{i} = L_{i}A_{i}\left(h_{i}^{\text{river}} - h_{i}^{\text{gw}}\right)$$
(9)

where Q_i is the volumetric flux between river and aquifer $[L^3 T^{-1}]$, L_i is leakage coefficient $[T^{-1}]$, A_i is the predefined area for each leakage node $[L^2]$, h_i^{river} is river stage [L] and h_i^{gw} is groundwater level underneath the river [L].

4 Synthetic experiments

The general setup of the synthetic experiments consists of the following steps:

- 1. Generation of ten spatially heterogeneous distributions of log(*L*) with sequential Gaussian simulation (SGS).
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- 2. Finite elements solution of the transient variably saturated flow equation (for 609 days) using SPRING. A solution is calculated for each of the ten generated log(L)-fields of step 1. The calculated hydraulic heads and river-aquifer exchange fluxes for these ten simulations serve as the ten "true" reference solutions.
- 5 3. Generation of log(L) ensembles (100 realisations) for a fully heterogeneous case and three different zonations (5, 3 and 2 leakage zones).
 - 4. For each of the ten references (step 1 and 2): Assimilation of hydraulic head data from step 2 with EnKF for the four log(L)-ensembles of step 3.

This procedure is used for three scenarios which differ in the degree of heterogeneity of $\log(L)$ reference fields and in the information content of the initial ensemble:

- A strongly heterogeneous log(L)-field for reference and initial ensemble
- B moderately heterogeneous log(L)-field for reference and initial ensemble
- C strongly heterogeneous log(L)-field with prior information in the initial ensemble

Scenario A serves as a base scenario for which the relevant results of the simulation experiments are presented in detail. The results for scenarios B and C are then discussed with respect to deviations from scenario A. In this sense, scenario B is utilized to assess the performance of data assimilation for different degrees of heterogeneity and scenario C should give insight into the value of prior information for the data assimilation with EnKF.

20 4.1 Reference fields

The reference fields of leakage coefficients for scenario A were generated by adding perturbation fields to a predefined mean value of log(L) of $-2.78 log(ms^{-1})$. The perturbation fields were generated by SGS with the code GCOSIM3D (Gómez-Hernández and Journel, 1993) for rivers Sihl and Limmat. These perturbation fields had a grid size



of 50 m. A spherical variogram was chosen for geostatistical simulations of the ten perturbation fields. The nugget was set to $0 \log(m s^{-1})$ for all simulations. The range of the variograms was sampled from a uniform distribution with values ranging from 1000 to 2000 m for each reference field. Values for the sill were also sampled from a uniform

⁵ distribution ranging from 1 to $2 \log(m^2 s^{-2})$. The simulated fields were directed onto the main axis of the rivers and the leakage coefficient for each river node $\log(L)$ was determined by the overlying grid block of the geostatistically simulated perturbation field plus the predefined mean value of $-2.78 \log(m s^{-1})$. The different reference fields of leakage coefficients are shown in Fig. 3 along the x-coordinate of the model domain.

¹⁰ For the creation of reference fields for scenario B a similar methodology as for scenario A was applied. The only difference between these two scenarios is that for scenario B a sill between 0.1 and 0.5 log(m²s⁻²) was used what results in a lower degree of variability for these references.

For scenario C the reference fields of log(L) have a predefined zonation with five leakage zones whose spatial location corresponds to the one of ensemble Z_5 (see below). The predefined zonal values for log(L) are summarized in Table 1. Similar to scenario A, perturbation fields were added to these predefined zonal values. These perturbation fields were created in a similar way as scenario A with a nugget of $0 log(m s^{-1})$, a sill of $1 log(m^2 s^{-2})$ and a range of 600 m. Compared to scenario A these reference fields include a higher contrast between different parts of the river reach (realized through the predefined zonation) and an additional component of interzonal variability (realized through the perturbation fields).

4.2 Zonation

For the assimilation experiments four ensembles of leakage coefficients were generated which differed in their spatial representation of heterogeneity. The first ensemble Z_{het} represents the full heterogeneity of the reference fields and the number of zones is equal to the number of river nodes (i.e., 457). The second ensemble Z_5 only represents 5 leakage zones which were positioned according to the main hydrological features of





the river reach (i.e., position of two weirs, confluence of rivers Sihl and Limmat) which results in four leakage zones for river Limmat and one leakage zone for river Sihl. For the third ensemble Z_3 river Limmat is divided into two leakage zones and river Sihl is the third leakage zone. For the fourth ensemble Z_2 river Limmat is aggregated to one leakage zone and again river Sihl serves as a separate leakage zone. The spatial arrangement of leakage parameters for the fully heterogeneous case (Z_{het}) and the three

zonation approaches (Z_5 , Z_3 and Z_2) is depicted in Fig. 4.

4.3 Ensemble generation

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The generation of the ensembles for Z_{het} for the three scenarios corresponded closely to the generation of the respective reference fields. However, a higher degree of uncertainty with respect to geostatistical parameter was used for the ensembles. For scenario A the range parameter varied between 50 and 5000 m and the sill value between 0.1 and 3.0 log(m²s⁻²). For scenario B the sill for Z_{het} has values between 0.1 and 1.5 log(m²s⁻²) and the range between 50 and 5000 m. For scenario C the ensemble for Z_{het} was generated with the same geostatistical parameters as for scenario A.

The ensembles for Z_5 , Z_3 and Z_2 for each scenario were generated on the basis of the respective ensemble for Z_{het} by calculating the arithmetic average of log(L) values for each realization of Z_{het} according to the respective zonation scheme. For example, the value of log(L) for one of the five leakage zones of Z_5 for a single realization is calculated from the corresponding realization of Z_{het} by averaging the log(L) of Z_{het} that are within the respective zone of Z_5 . This procedure is then repeated for all leakage zones and all realizations of Z in Fig. 5 the generated ensembles for scenario A are

zones and all realizations of Z_5 . In Fig. 5 the generated ensembles for scenario A are compared to reference field I.

4.4 Settings for data assimilation with EnKF

²⁵ The meta parameters for data assimilation experiments for scenario A, B and C with EnKF are summarized in Table 2. For all three scenarios 100 observation points were



used as input data for EnKF. Scenario A was additionally simulated with a lower amount of observations (10 measurements). The other settings for assimilation with EnKF were held constant for all scenarios.

4.5 Performance assessment of simulations

⁵ The performance of the data assimilation experiments is assessed by the prediction error of hydraulic heads throughout the model domain, the prediction error of river-aquifer exchange fluxes and the correction of leakage coefficients during the update. For the prediction error of hydraulic heads the root mean square error (RMSE_h) between the predicted mean hydraulic head and the hydraulic head of the reference is calculated using:

$$\text{RMSE}_{h}(t) = \sqrt{\frac{1}{n_{\text{nodes}}} \sum_{i}^{n_{\text{nodes}}} \left(\overline{h}_{i}(t) - h_{i}^{\text{ref}}(t)\right)^{2}}$$

where \overline{h}_i is the mean hydraulic head for model node *i* [L], h_i^{ref} is the hydraulic head of the reference simulation for node *i* [L], n_{nodes} is the total number of model nodes and *t* is time step [T].

For the evaluation of river-aquifer exchange we present either the evolution of the leakage fluxes over time Q(t) or statistics for the total volume of water that was exchanged between river and aquifer during the whole simulation period ΔV_{tot} :

$$Q(t) = \sum_{i}^{\text{box}} Q_i(t) \tag{11}$$

²⁰
$$\Delta V_{\text{tot}} = \sum_{j}^{t_{\text{tot}}} \sum_{j}^{n_{\text{leak}}} Q_{ij} \Delta t_{j}$$

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where Q(t) is the river-aquifer exchange flux over time $[L^{3}T^{-1}]$, $Q_{i}(t)$ is the leakage flux for river node *i* over time, n_{leak} is total number of leakage nodes, ΔV_{tot} is the volume of water that is exchanged between river and aquifer over the whole simulation period $[L^{3}]$, Q_{ij} is the volumetric flux between river and aquifer for the *i*th leakage node and the *j*th time step $[L^{3}T^{-1}]$, Δt_{j} is time step [T] and t_{tot} is total number of time steps. Q(t) was calculated direction dependent, i.e., fluxes from river to aquifer (positive) and fluxes from aquifer to river (negative) were summed up separately.

5 Results

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5.1 Strongly heterogeneous case (scenario A)

Figure 6 compares $RMSE_h$ of the four log(L)-ensembles for ten highly heterogeneous reference fields (scenario A). The highest improvement is observed for Z_{het} where $RMSE_h$ is consistently reduced to about 0.1 m among all references. For the other ensembles the performance in terms of $RMSE_h$ is more dependent on the specific reference. For example, $RMSE_h$ of Z_5 is similar to the one of Z_{het} for some references (e.g., IV, VIII and X) but is worse for other references (e.g., II and IX). A similar behavior can be observed for Z_3 and Z_2 .

The updated net fluxes between river and aquifer are shown in Fig. 7 for reference field I. For this reference field the updating with EnKF led to an improvement of the prediction of fluxes from river to aquifer for all four ensembles. Fluxes from aquifer to river were well reproduced by Z_{het} and Z_5 whereas for Z_3 and Z_2 a larger deviation between ensemble mean and true values was found. The ensemble variance of leakage fluxes decreases very fast where most of the decrease happens in the first 100 simulation days. One exception is the flux from aquifer to river for Z_{het} . The general decrease of variance within the first 100 days is observable for all ten references whereas the

higher variability for Z_{het} was a special feature of reference I.





An overview of the net exchange between river and aquifer for all ten references is given in Fig. 8. Here the total amount of exchanged water summed over the complete simulation period (ΔV_{tot}) is displayed for each of the reference fields and for each of the zonation approaches. The net exchange for Z_{het} is very close to the net exchange of the respective reference and thus shows the best performance among the four ensembles. Z_5 is usually also very close to the net exchange of the references except for reference III where the net flux is greatly underestimated by this ensemble. Z_3 and Z_2 show a good fit for some references (e.g., reference IV) but the fluxes are significantly overor underestimated for other references.

- Figure 9 gives an example of the spatial distribution of exchange fluxes for time step 300 and reference IV. For Z_{het} the spatial distribution of exchange fluxes of the reference run is principally captured by the ensemble and the exchange fluxes of the reference run are within the uncertainty bounds of the ensemble. For Z_5 , Z_3 and Z_2 some of the principal features of the reference run, i.e., the river parts with the highest positive exchange fluxes, are also present although the reference fluxes are not any
- more within the uncertainty bounds of the zonated ensembles. In other parts of the river the exchange fluxes of the reference run are not present in the ensemble calculations of Z_5 , Z_3 and Z_2 , e.g., the negative fluxes in the western part of the model.

Figure 10 compares the initial ensembles of leakage coefficients with the updated ones at day 600 for reference I. In general, the updated ensembles at time step 600 have a smaller variance than the initial ensembles. For Z_{het} the updated log(L)ensemble mostly covers the spatial pattern of the reference field. In some parts of the river Z_{het} still has a relatively high variance while in other parts variance is low and the spatial pattern of the ensemble is close to the pattern of the reference field. For Z_5 the

²⁵ mean values for the different zones remain more or less constant during the updates while the ensemble variance for the different zones strongly decreases for four of the five zones. For Z_3 and Z_2 also a very strong decrease in ensemble variance is visible.





5.2 Strongly heterogeneous case with lower observation density

In order to investigate how a lower density of observation points affects the results for the different zonation approaches the assimilation experiments for the first five reference fields of scenario A were repeated with hydraulic head time series measured at only 10 points instead of 100. The overall error in terms of RMSE_h for Z_5 , Z_3 and Z_2 was comparable to the ones in the assimilation experiments with 100 observation points. For Z_{het} the overall deviations to the reference were slightly higher when only 10 observation points were used but predictions were still slightly better than for the zonated ensembles. For Z_{het} the predicted mean fluxes in both directions (i.e., fluxes to river or to aquifer) were underestimated in most cases whereas there were no major differences for the other ensembles. Flux predictions for Z_{het} were also associated with a higher degree of uncertainty compared to the assimilation of 100 observations. Despite an underestimation of both fluxes from river to aquifer and fluxes from aquifer to river for Z_{het} the predicted net fluxes between river and aquifer were comparable to the assimilation with 100 observation points.

- to the simulations with 100 observation points, i.e., Z_{het} gave good results for all references. Net fluxes for the other ensembles were also similar to the assimilation of 100 measurements and especially for Z_3 and Z_2 higher deviations occurred for some references. The update of leakage coefficients for Z_{het} was not as good as for the assimilation of 100 observations. The main structural features of the reference fields were
- ²⁰ captured during the assimilation but the ensemble variance at the end of the simulation period was significantly higher when only 10 observations were assimilated (see Fig. 11). From Fig. 11 it becomes obvious that there are more extreme values than for the assimilation of 100 observations. This can be seen as a reason for the higher variability of fluxes for Z_{het} . The variability of $\log_{10}(L)$ for the other ensembles increased only marginally and also the mean values for Z_3 and Z_2 were similar to the assimilation
- only marginally and also the mean values for Z_3 and Z_2 were similar to the assimilat of 100 measurements.





5.3 Mildly heterogeneous case (scenario B)

compared to scenario A (Fig. 13).

For scenario B the variability of log(*L*)-fields for the references and the initial ensembles was reduced. Results for this case show that RMSE_h for Z_5 , Z_3 and Z_2 correspond more closely to RMSE_h of Z_{het} . Nevertheless, Z_{het} still shows the best performance

- ⁵ in terms of RMSE_{h} for all ten references. The temporal evolution of leakage fluxes for the ten references is captured well by all four ensembles. Compared to scenario A the systematic differences that occurred between reference fluxes and simulated fluxes were reduced (especially for Z_3 and Z_2). This is also reflected in the cumulative net exchange over the simulation period (Fig. 12).
- It can be seen that ensembles are generally closer to the reference values and this is especially pronounced for Z₃ and Z₂. But still there are some references where the uncertainty bounds of Z₂ do not cover the reference flux. Although the prediction of cumulative net fluxes for scenario B is better for ensembles with a lower number of leakage zones the spatial representation of fluxes is still worse for Z₂, Z₃ and Z₅
 than for Z_{het} where the spatial distribution of leakage fluxes closely corresponds to the reference fluxes.

5.4 Strongly heterogeneous case with a predefined zonation (scenario C)

In scenario C the references include a predefined zonation with a relatively high contrast of log(*L*) between the individual zones. A second important feature of this scenario is that for Z_5 the location of leakage zones is similar to the ones of the references. Thus the initial ensemble of Z_5 includes prior information on the spatial distribution of log(*L*). RMSE_h of Z_{het} and Z_5 are very similar for this scenario with slightly lower errors for Z_{het} . In contrast, Z_3 and Z_2 perform worse in terms of RMSE_h compared to scenario A. For the net fluxes between river and aquifer a similar relation is found. Again Z_{het} and Z_5 show relatively similar values which are very close to the reference values whereas Z_3 and Z_2 consistently underestimate the net exchange what leads to a higher error



The general worse performance for Z_3 and Z_2 in terms of head and flux predictions is a consequence of the spatial averaging of $\log(L)$. For the ensembles used for scenario C the spatial contrasts for $\log(L)$ are higher due to the predefined zonation in the references and initial ensembles. Therefore, the leakage zones of Z_3 and Z_2 cover parts of the reference fields that have very different $\log(L)$ -values. This can be seen in Fig. 14 where the initial $\log(L)$ ensemble is compared with the updated one at the end of the simulation period. Because Z_3 and Z_2 are not flexible enough to account for the variability of the references due to their limited number of leakage zones the simulated piezometric heads and leakage fluxes deviate more strongly from the reference values than Z_{het} and Z_5 .

6 Discussion

Simulations with EnKF generally lead to an improvement for all four ensembles in terms of $RMSE_h$. It was found that a stochastic field approach (i.e., each discretization point of the model grid might have a different leakage value, which results in 457 values in this study) gave the best results. Data assimilation with EnKF made it possible to correct the cumulative fluxes between river and aquifer almost completely. For Z_{het} also the spatial distribution of log(L) gets quite close to the reference fields during data assimilation and this is also reflected in the spatial distribution of exchange fluxes which closely coincides with those of the reference runs. Data assimilation results in

- ²⁰ a decrease of the variability of log(L) especially in regions with high exchange fluxes between river and aquifer. In other river regions where exchange fluxes are not so high the uncertainty regarding log(L) was reduced compared to the initial ensemble but not to the same extent as for regions with a higher net flux. The lower adaptation of log(L) in regions of low exchange fluxes is probably a consequence of the lower sensitivity of the
- ²⁵ parameter update on head measurements, i.e., for low exchange fluxes the correlation between hydraulic heads and log(L) is low what leads to a lower degree of adaptation for log(L). The opposite applies for regions with higher fluxes where the adaptation





of model parameters is better constrained what leads to a lower variability of model parameters in the end of the simulation period.

For the three zonated ensembles the overall performance was usually slightly worse than for the ensemble with full heterogeneity. Especially the net fluxes showed significant deviations from the true values for Z_3 and Z_2 for several references. This is reflected in the spatial distribution of fluxes along the river where regions with higher fluxes in the reference runs were not adequately represented by the ensembles Z_3 and Z_2 . EnKF was only partly able to correct for the systematic errors that arose from the wrong spatial distribution of exchange fluxes and as a result of this the prediction of net fluxes was not as good as for Z_{het} . For Z_5 the predicted net fluxes were often similar to the ones of Z_{het} but the spatial distribution of fluxes was not as good as for Z_{het} . This was also the case when Z_5 closely matched the spatial distribution of log(L) of the reference runs (scenario C). Even with this prior information only the net fluxes were

estimated correctly but not their spatial distribution. This also applies for references
¹⁵ with a lower degree of heterogeneity (scenario B). Even in this case the predicted spatial distribution of leakage fluxes was better with Z_{het} than with the different zonation approaches. However, a precise estimation of high local leakage fluxes is highly relevant for transport calculations in order to determine source regions of contaminants or regions of high biogeochemical turnover. For these applications the usage of effective
²⁰ parameters thus will only lead to averaged concentration levels that are derived from the net exchange between river and aguifer.

For a lower observation density (10 measurement locations) the results were not very different from the ones for 100 observation points. However, for Z_{het} the uncertainty in the log(*L*)-ensemble was larger than for the case with 100 measurement data.

²⁵ As a result of this also the uncertainty regarding the exchange fluxes was higher. Nevertheless, the error in head and flux predictions was still equal or better than for the zonated ensembles. Generally, a lower information content did not significantly affect the identification of the leakage parameters and the prediction of fluxes and states.





The results from these synthetic studies suggest that the high-resolution characterization of river bed properties is feasible, because even with a limited number of measurements, the high-resolution reconstruction resulted in better results than an approach where the spatial variability of the river bed was represented with a few effective

- ⁵ parameters only. We expect that in case only very few measurements are available, high-resolution and zonation approaches might give predictions of similar quality, and that in case of more measurements the high-resolution approach will increasingly outperform the approaches where only a few effective parameters are estimated. It can be important to condition multiple equally likely stochastic high-resolution realizations of
- river bed properties, because the quality of the estimated net exchange fluxes between aquifer and stream are better with this approach than with a zonation approach. Replacing the heterogeneous streambed with few effective parameters results in biased predictions of exchange fluxes. Over long streams such a systematic bias might result in an important under- or overestimation of the groundwater infiltration in the river, as
- ¹⁵ well as an under- or overestimation of the loss of river water to the aquifer under flood conditions. Therefore, we recommend the calibration of equally likely stochastic realizations of river bed properties using EnKF together with an augmented state vector approach, for a better characterization of river-aquifer exchange fluxes. This approach is especially needed in case of very heterogeneous streambeds and in case enough conditioning measurements (hydraulic head data) are available.

Of course, our findings were derived on the basis of a simplified model which only accounts for uncertainties regarding leakage parameters. In real-world applications uncertainties also arise from the poorly known distribution of aquifer properties, model structural errors and uncertainties in the determination of forcing terms for the model.

²⁵ Thus the calibration of log(L)-distributions with EnKF in real-world cases will probably not be as confident as in our synthetic simulations due to the higher overall uncertainties. Nevertheless, the principal differences between a heterogeneous ensemble and an ensemble of effective parameters will remain because of the higher flexibility of the heterogeneous approach.





7 Conclusions

In this study we performed data assimilation experiments with a synthetic rivergroundwater interaction problem where piezometric heads and heterogeneous river bed conductivities were jointly updated with the Ensemble Kalman Filter (EnKF). In this

- ⁵ context, different parametrizations of river bed heterogeneity (full heterogeneity versus different amounts of effective parameters) were tested for their effect on the prediction of groundwater levels and river-aquifer exchange fluxes. A high resolution representation of the river bed hydraulic conductivities (compared to a coarse representation with constant values in a few zones) results in a better characterization of stream-aquifer
- exchange fluxes, both in terms of the net exchange between the two compartments and the spatio-temporal distribution of this exchange. When the river was divided in a relatively limited number of leakage zones (2, 3 or 5) the net exchange between river and aquifer was not predicted accurately for all references and in general the errors increased with a decreasing representation of heterogeneity. In case of a reduced
- amount of head observations (10 instead of 100), the high resolution calibration of river bed conductivities still outperformed the scenarios with a coarse representation of river bed conductivities. However, differences between the scenarios were smaller.

In summary, it is concluded that a zonation of river bed conductivities should be avoided because small regions with high exchange fluxes might be averaged out by

- ²⁰ zonation what affects the local water balance. We recommend therefore that for highly heterogeneous river beds a geostatistical simulation approach is used where river bed properties change from grid cell to grid cell. Our simulations showed that parameter updates with EnKF are able to adapt an ensemble of such high resolution fields of river bed conductivity towards the true reference field. Furthermore, the CPU demand for
- ²⁵ parameter adaptation with EnKF is not dependent on the number of defined leakage zones as opposed to other calibration techniques. This approach will also avoid a bias in the estimation of the regional water balance.





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Table 1. Predefined zonal leakage values for generation of reference fields for scenario C.Leakage zones are numbered from west to east.

| leakage zone | $\log_{10}(L_{zonal}) [\log_{10}(m s^{-1})]$ |
|--------------|--|
| I | -5.51 |
| II | -1.96 |
| III | -3.88 |
| IV | -5.37 |
| V | -6.44 |



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Table 2. Default settings for data assimilation with EnKF.

| parameter | value |
|-------------------------|----------|
| ensemble size | 100 |
| observation points | 100 (10) |
| damping factor α | 0.1 |
| update frequency | 10 days |
| measurement error | 0.05 m |



Fig. 1. Schematic representation of model domain and boundary conditions.





Fig. 2. Forcing data for synthetic experiments. Represented are total amounts of artificial recharge, extraction from bank filtration and extracted drinking water (left), as well as river discharges (middle) and total recharge amount over the study domain (right), for a period of 609 days (January 2004–August 2005).











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Fig. 4. Spatial representation of heterogeneity for four parameter ensembles. In the fully heterogeneous case (Z_{het}) an individual leakage coefficient is assigned to each river node. For the zonated ensembles $(Z_5, Z_3 \text{ and } Z_2)$ each colour corresponds to a separate leakage zone. The river nodes within a leakage zone share the same leakage coefficient.









Fig. 6. RMSE_{h} of conditional simulations with EnKF for ten reference fields of leakage coefficients (scenario A). Four different ensembles are compared. EnKF jointly updated hydraulics heads and leakage coefficients with measurement data from 100 observation points.





Fig. 7. Cumulative directional fluxes between river and aquifer for conditional simulations with EnKF for four representations of spatial heterogeneity (scenario A). Results are shown for reference I. Fluxes from river to aguifer have a positive sign.



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Fig. 8. Total amount of water exchanged between river and aquifer over the whole simulation period (609 days) for scenario A. Red lines mark the water exchange for the different reference runs. On the right hand side the description of the boxplots is illustrated.





Fig. 9. Fluxes between river and aquifer along X-axis of model domain for conditional simulations with EnKF at simulation day 300 (scenario A, reference IV). Fluxes from river to aquifer have a positive sign.





Fig. 10. Ensembles of leakage coefficients (coloured) and reference field (black) along X-axis of model domain at day 1 (upper row) and at day 600 (lower row) for scenario A.



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Fig. 12. Total amount of water exchanged between river and aquifer over the whole simulation period (609 days) for conditional simulations with EnKF (scenario B). Red lines mark the water exchange for the different reference runs.





Fig. 13. Total amount of water exchanged between river and aquifer over the whole simulation period (609 days) for conditional simulations with EnKF (scenario C). Red lines mark the water exchange for the different reference runs.





Fig. 14. Ensembles of leakage coefficients (coloured) and reference field (black) along X-axis of model domain at day 1 (upper row) and at day 600 (lower row) for scenario C.



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