

## **General concern about our use of uncorrelated conductivity fields:**

Since both referees commented on this, we are responding to them together.

The reviewers correctly point out that hydraulic conductivity is a random field; furthermore, it is correlated at some scales. Indeed, the effect of small-scale correlations on regional velocities and mass transport is completely understood at least through second-order (Gelhar and Axness, 1983; Winter et al., 1984; Neuman and Orr, 1992), and there is no doubt that scaled up regional velocities can be affected by the degree of correlation between conductivities at small scales, even when the conductivity field is heterogeneous at local and regional scales (Winter and Tartakovsky, 2002). But the degree of correlation, and hence its effect on regional velocities and quantities like stream-aquifer exchanges that are influenced by them, depends on the meaning of "small". The small scale of our study is set by the 1 km x 1 km size of our grid cells. Many alluvial systems have correlation lengths that are much smaller than that, e.g., Rehfeldt et al. (1992) and Riva et al. (2006), so at the "small" scale of our study, which is typical of simulations used to support regional watershed management, conductivities are effectively uncorrelated in some real settings. Hence, it is informative, and in some cases realistic, to investigate the effect that a field of independent, identically distributed conductivities has on the state variables of regional models. Our experiments show that stream-aquifer exchanges estimated by a typical regional simulation (one that ignores local heterogeneity) can be biased even when local conductivities are uncorrelated. We agree with the reviewers that more remains to be done with regard to the study of locally correlated fields, and we (and we hope others) are at work on such studies. But the work must start somewhere, and it seems sensible to start with the maximum entropy model: one like ours that makes the fewest assumptions about the structure of conductivity, yet is relevant to watershed management. We hope the reviewers and editor will agree that such a model provides a baseline for additional studies and is useful in its own right. If the reviewers and editor believe it will help, we will be glad to put a discussion to this effect in our paper.

## **Responses to Referee #1:**

Thank you very much for your comments. We paid careful attention to your concerns and respond to each of them as follows.

### **(1) Main concern: Justify the assumption of uncorrelated conductivity fields.**

- This is clearly a critical issue. Please see above.

We added a paragraph to response the comments about why it makes sense to study

the influence of uncorrelated fields.

**(2) Line 25 on Page 5: Does “second” follow “First” in Line 19 of Page 5?**

- Yes, “second” in Line 26 of Page 5 follow “First” in Line 18 of Page 5. We put them into the same paragraph in the reversed manuscript.

**(3) Line 20 on Page 12: Is this conclusion based on Figure 2c?**

- This conclusion is based on Fig. 2a and 2b, so we added reference here in the revised version.

**(4) It is better to add a dashed zero-line on Figure 2c so that the differences of groundwater table below (or above) 0 can be explicitly shown.**

- There are two vertical axes in Fig. 2c, and their scales are different. The groundwater table changes are much larger than river stage changes, so it may not be necessary to add a dashed zero-line. We will follow the advice of the editor and reviewer regarding modifying this figure, but we have left it the same for now

**(5) Figure 3b is a little hard to read. It is suggested to use gray color for water table depth and improve the contrast with monthly leakage data.**

- Using gray color for water table depth is better to improve the contrast with monthly leakage data, but it is not so easy to see the distinct groundwater table changes. As we tried to demonstrate that the groundwater table distribution affects the groundwater flow rate distribution and stream-aquifer exchanges in the later text, it seems better to highlight the colorful water table depth. We will follow the editor's and reviewer's further advice on this point.

**(6) Line 2 on page 15: Is this confidence interval computed based on 10 realizations generated using equation (1) and (2)? Is the realization number sufficient to make a reasonable statistics?**

- Yes, this confidence interval, computed based on 10 realizations, is generated using equations (1) and (2). We have compared the different realization results, and found they are almost the same with more realizations. So 10 realizations seem sufficient to make a reasonable statistics. We have added a statement to this effect in our paper.

## **Responses to Referee #2:**

Thank you very much for your comments and suggestions. Based on them, we revised the paper carefully, and we respond to each of your comments in the following.

### **General comments**

**(1) The Authors simulate the regional exchanges of water between stream and aquifer systems using a two-dimensional (single-layer) flow model. And they assume the streambed conductance the same for all simulations. The results of the mathematical model could be a little more realistic respect to the Middle Heihe River Basin (MHRB) and they cannot contribute to the management of water resources in this area.**

- We used a two-dimensional (single-layer) flow model to simulate the regional exchanges of water between stream and aquifer systems because that is standard practice in watershed management and it is the one that we wish to test for bias, etc. in this study; in that sense, we are using the MHRB as a convenient example. With regard to the Heihe River Basin specifically, Hu et al. (2007) state that vertical flow is significant in the study area, but water exchanges are more influenced by the connected stream and aquifer system, which means we can treat all layers as a whole. It is also questionable how many layers truly exist. Since our study focuses on comparing the effects of heterogeneous conductivity (or transmissivity, if that is preferred) to a typical two-dimensional model used in many applications of groundwater modeling to water resources management, we have used a single layer.

Additionally, several studies indicate that aquifer heterogeneity influences water exchanges more strongly than do variations in the streambed (Woessner, 2000; Fleckenstein et al., 2006; Kalbus et al., 2009). Our focus on sensitivity to the effects of locally heterogeneous hydraulic conductivity, led us to hold streambed conductance constant across realizations. Since the locally heterogeneity of streambed conductance is affected by many factors (landform, river morphology, sediment, et al.) in different time and space, its effects are much more complicated than those of aquifer heterogeneous conductivity and will need further study. For now, it seems reasonable to stick to experiments with one control variable, the level of heterogeneity in the conductivity field.

The results of the mathematical model can reveal these non-linear effects and contribute to the understanding of aquifer heterogeneity effects on stream-aquifer water exchanges. The calibration results showed the numerical model for the MHRB

could simulate the groundwater movement and water cycle relatively satisfactorily, and it reflects realistic conditions in the MHRB. Since stochastic computational tools are more and more capable of approximating the range of dynamics of basin-scale hydrologic systems, we believe the results will also contribute to the management of water resources in this area.

**(2) The assumption of random hydraulic conductivities uncorrelated in space is questionable, and a great CV could be not so consistent with the heterogeneity patterns of the aquifer.**

- Our discussion of the relevance of uncorrelated random conductivity fields is given above. We added a paragraph to response the comments about why it makes sense to study the influence of uncorrelated fields.
- The Coefficient of Variance (CV) quantifies the level of aquifer conductivity heterogeneity (refer to Kalbus et al. (2009), for example). Levels of  $CV = 2$ , and indeed much higher, are frequently found in groundwater studies, and indeed can be a serious limitation for approximations based on perturbation expansions when the perturbation parameter depends on the variance of the conductivity field (cf., Zhang, 1998).

**(3) They assume, among the others, that i) small-scale heterogeneities of hydraulic conductivity significantly affect simulated stream-aquifer water exchanges in river basins and ii) systematic biases arise in estimates of exchanges if small-scale heterogeneities are smoothed by aggregation into a few sub-regions. With these assumptions they try to prove, by means of computational experiments, that the biases result from slow-paths in groundwater flow that emerge due to small-scale heterogeneities.**

- We are sorry to have been unclear: First, the points identified above as (i) and (ii) are hypotheses (called H1 and H2 in our paper) that we test through our computational experiments. They are important in themselves, since they add weight to the practical conclusion that watershed management decisions based on typical deterministic models, e.g., the base case of our paper, may over-estimate exchanges of water between aquifers and streams, especially aquifer discharge. They also motivate hypothesis H3, that local heterogeneity of conductivity produces slow paths in the local flow field. We do not mean to imply that our experiments "prove" anything, since it is not possible to do that with a few experiments; only the weight of evidence produced by many experiments can do anything like that. We actually make a comment similar to this in our concluding remarks, but we will be happy to amplify that, and other such discussions in our paper, if the editor and

reviewer believe that is needed.

### Specific Comments

**(1) Line 6 on page 4:** “The zones were defined in previous hydrogeological studies of the MHRB (Hu et al., 2007): but in their work, Hu et al. divide the aquifer in 8 layers. Could be, please, more precise?

- There were 8 layers in their work of Hu et al., and we adopt the thickest layer (Layer Six), which can most represent the aquifer properties in space. This layer in their work also had relatively more zones than other layers.

**(2) In section 2.2 the author state “All stream–aquifer interactions are simulated using the numerical modeling tool MODFLOW with the stream package (STR) for one-dimensional stream flow and two dimensional groundwater flow”: I suppose that is true for this study and not for all. And after “..... This is an acceptable assumption for typical alluvial sediments of the kind found in the MHRB (Spanoudaki et al., 2009; Huang, 2012)": this assumption depends on the objective study too!**

- Line 12 on page 8: Thanks for your idea. It is true for this study and not for all. This assumption also depends on our objective study, so we corrected it in the manuscript.

**(3) Line 21 on page 8: I suppose that seepage was calculated from the product of the head difference times the streambed conductance.**

- Thanks for your suggestion. That is right, and we corrected this in the revised manuscript.

**(4) Line 12 on page 9: “Stream inflow at the YLX Gauge and groundwater lateral recharges from mountain areas are used as an upper boundary, and outflow at the ZYX Gauge is taken as a lower boundary (Zhou et al., 2011)": Explain as these flowrates were estimated.**

- The stream inflow at the YLX Gauge ( $15.8 \times m^3/a$ ) and out flow at the ZYX Gauge ( $9.5 \times m^3/a$ ) are collected from the observed runoff data. In their study, there were lateral recharges from mountain areas, which can be obtained from the total water resources quantity and surface river inflow amounts.

**(5) Figure 2c), is the legend correct?**

- Yes, the legend is correct. The horizontal axis represents the distance from the upper boundary (i.e. YLX) along the river. The left vertical axis represents the river stage changes in December, compared with that in June. The right vertical axis represents the groundwater table changes for each corresponding cell along the river. We added a bit more explanation to make this more explicit.

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2 **author's changes in manuscript:**  
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4 **Nonlinear effects of locally heterogeneous hydraulic  
5 conductivity fields on regional stream-aquifer exchanges**

6 Jinfeng Zhu<sup>1</sup>, C Larrabee Winter<sup>2,\*</sup>, Zhongjing Wang<sup>1,3,\*</sup>

7 <sup>1</sup> Department of Hydraulic Engineering, Tsinghua University, Beijing, 100084, China

8 <sup>2</sup> Department of Hydrology and Water Resources and Program in Applied

9 Mathematics, University of Arizona, Tucson, AZ, 85721, USA

10 <sup>3</sup> State Key Laboratory of Hydro-Science and Engineering, Tsinghua University, Beijing,

11 100084, China

12

13

14 \*Corresponding author information:

15 Email: [winter@email.arizona.edu](mailto:winter@email.arizona.edu)

16 Tele: +1 520 621 7120

17 Email: [zj.wang@mail.tsinghua.edu.cn](mailto:zj.wang@mail.tsinghua.edu.cn)

18 Tele: +86 10 62782021

19

20 Manuscript submitted to *Hydrology and Earth System Sciences*

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22

1    **Abstract**

2    Computational experiments are performed to evaluate the effects of locally  
3    heterogeneous conductivity fields on regional exchanges of water between stream and  
4    aquifer systems in the Middle Heihe River Basin (MHRB) of northwestern China.  
5    The effects are found to be nonlinear in the sense that simulated discharges from  
6    aquifers to streams are systematically lower than discharges produced by a base  
7    model parameterized with relatively coarse effective conductivity. A similar, but  
8    weaker, effect is observed for stream leakage. The study is organized around three  
9    hypotheses: (H1) small-scale spatial variations of conductivity significantly affect  
10   regional exchanges of water between streams and aquifers in river basins, (H2)  
11   aggregating small-scale heterogeneities into regional effective parameters  
12   systematically biases estimates of stream-aquifer exchanges, and (H3) the biases  
13   result from slow-paths in groundwater flow that emerge due to small-scale  
14   heterogeneities. The hypotheses are evaluated by comparing stream-aquifer fluxes  
15   produced by the base model to fluxes simulated using realizations of the MHRB  
16   characterized by local (grid-scale) heterogeneity. Levels of local heterogeneity are  
17   manipulated as control variables by adjusting coefficients of variation. All models are  
18   implemented using the MODFLOW simulation environment, and the PEST tool is  
19   used to calibrate effective conductivities defined over 16 zones within the MHRB.  
20   The effective parameters are also used as expected values to develop log-normally  
21   distributed conductivity ( $K$ ) fields on local grid scales. Stream-aquifer exchanges  
22   are simulated with  $K$  fields at both scales and then compared. Results show that the  
23   effects of small-scale heterogeneities significantly influence exchanges with  
24   simulations based on local-scale heterogeneities always producing discharges that are  
25   less than those produced by the base model. Although aquifer heterogeneities are  
26   uncorrelated at local scales, they appear to induce coherent slow-paths in groundwater  
27   fluxes that in turn reduce aquifer-stream exchanges. Since surface water-groundwater  
28   exchanges are critical hydrologic processes in basin-scale water budgets, these results  
29   also have implications for water resources management.

30

1    **1. Introduction**

2    Exchanges of water between streams and aquifers are critical elements in the  
3    coupled dynamics of watersheds. Groundwater discharge to streams maintains natural  
4    hydrologic systems through base flow during periods of low stream flow, while  
5    leakage from streams is an important source of groundwater recharge (Sophocleous et  
6    al., 1995; Hantush, 2005; Newman et al., 2006). The magnitudes of such fluxes vary  
7    on scales ranging from sub-regional (or zonal) to local scales. Local variations in  
8    the spatial distribution of aquifer characteristics are known to affect groundwater flow  
9    and stream-aquifer exchanges on sub-regional scales (Schmidt et al. 2006; Kalbus et  
10   al., 2009; Mendoza et al., 2015), but it is not usually possible to measure system  
11   parameters and states with sufficient accuracy and level of detail to specify local  
12   variations throughout a watershed (Wroblicky et al., 1998; Kalbus et al., 2006).  
13   Furthermore, hydrologic system parameters can vary on multiple spatial and temporal  
14   scales and are subject to experimental error (Molz, 2000; Genereux et al., 2008).

15   Computational experiments, on the other hand, allow the effects of heterogeneity  
16   to be investigated by consistently varying the values of parameters, such as hydraulic  
17   conductivity, as control variables and observing the resulting effects on simulated  
18   system states (Winter et al., 2004; Bruen and Osman, 2004; Hantush, 2005). In this  
19   study the sensitivity of regional hydrologic systems to locally heterogeneous aquifer  
20   hydraulic conductivity is explored by simulating stream-aquifer exchanges in the  
21   Middle Heihe River Basin (MHRB) of northwestern China, a typical semi-arid basin.  
22   Fluxes in alluvial aquifers of the MHRB are usually represented as two-dimensional  
23   processes (Huang, 2012).

24   In addition to their importance for water resources management, stream-aquifer  
25   exchanges are a convenient measure of overall watershed performance because they  
26   summarize the states of system fluxes at well-defined locations where they are  
27   relatively easy to quantify. Two scales of heterogeneity are represented in the  
28   simulations, zonal and local (or grid-scale). Local-scale conductivity is manipulated  
29   as the only control variable in the computational experiments. All other system

1 parameters, including streambed conductance, are the same in every simulation.

2 Multi-physics models of the coupled hydrologic fluxes of the MHRB are  
3 implemented using the MODFLOW simulation environment ([McDonald and](#)  
4 [Harbaugh, 2003](#)). The PEST tool ([Doherty et al., 1994](#)) is used to calibrate an  
5 effective aquifer hydraulic conductivity for each of sixteen zones within the MHRB.  
6 The zones were defined in previous hydrogeological studies of the MHRB ([Hu et al.,](#)  
7 [2007](#)). The effective zonal parameters are also used as expected values to develop  
8 realizations of log-normally distributed conductivity fields on local grid scales.  
9 Standard deviations are defined by means of coefficients of variation (CV) ranging  
10 from 0.5 to 2.0. Ten realizations of a random conductivity field are produced for each  
11 CV. Random conductivity values are uncorrelated in space. Monthly stream-aquifer  
12 exchanges are calculated for each realization and for the zonally parameterized model.

13 The study is organized in terms of three explicit hypotheses about the effects of  
14 local-scale heterogeneity:

15 **H1.** Local-scale heterogeneities significantly affect regional  
16 stream-aquifer water exchanges in the MHRB.

17 **H2.** Systematic biases arise in estimates of stream-aquifer exchanges if  
18 local-scale heterogeneities are smoothed by aggregating conductivity into  
19 effective values for the set of 16 sub-regional zones.

20 **H3.** The biases are the result of slow-paths in groundwater flow that  
21 emerge due to small-scale heterogeneities in conductivity fields.

22 The hypotheses H1-3 are tested by comparing simulated stream-aquifer exchanges  
23 produced by the local realizations to the zonal simulation.

24 Hypotheses related to H1 and H2 have been investigated in a few recent studies.  
25 [Kalbus et al. \(2009\)](#) evaluated the relative effects of aquifer conductivity and  
26 streambed conductance by simulating stream-aquifer interactions in a 220m reach of a  
27 small stream in Germany. They found that heterogeneity in the aquifer influenced  
28 discharge to the stream more strongly than did variations in the streambed itself.

1 Schmidt et al. (2006) also studied the spatial distribution and magnitude of  
2 groundwater discharge to a stream with a simple analytical model that was mainly  
3 focused on groundwater discharge at the reach scale. Kurtz et al. (2013) generated  
4 multiple realizations of stream-aquifer interactions in the Limmat aquifer system in  
5 Zurich Switzerland. They allowed riverbed hydraulic conductivities to take one of  
6 four different levels of heterogeneity ranging from local variability at each grid-point  
7 to effective conductances of only 5, 3, and 2 values. They found that effective  
8 conductance did not always reproduce fluxes obtained from base simulations where  
9 system parameters were perfectly known, and furthermore, simulations based on  
10 effective parameters gave biased estimates of net exchanges between aquifer and  
11 stream. Mendoza et al. (2015) used a land surface model with strong a priori  
12 constraints on parameters to argue that such models can perform poorly when spatial  
13 variability and hydrologic connectivity of a region are represented coarsely. Lackey et  
14 al. (2015) used a synthetic stream-aquifer system to show that modeling streambed  
15 conductance as a homogeneous property can lead to errors in estimated stream  
16 depletion.

17 The current study contributes to the understanding of these topics in two ways.  
18 First, results indicate that locally heterogeneous hydraulic conductivity fields lead to  
19 systematic reductions of regional stream-aquifer exchanges, especially in the direction  
20 of aquifer-stream discharges. The causal mechanism appears to be slow paths that  
21 emerge in groundwater flows in response to local heterogeneities. These local-scale  
22 fluxes are spatially coherent and are not averaged out by aggregating conductivity into  
23 a few effective zonal parameters. The nonlinear effects of these coherent structures  
24 are propagated to regional scales. Second, hypotheses H1-3 have practical  
25 implications for allocations of water resources since many resource management  
26 decisions depend on the results of computational models like the base model used  
27 here (Perkins and Sophocleous, 1999; Fleckenstein et al., 2006). A regional basin is  
28 partitioned into a few zones, on the basis of physical, geographical and geological  
29 criteria (Eaton, 2006), and effective zonal parameters are set by calibration

批注 [Jinfeng1]: Following Referee#1's concern, we merged this two paragraphs.

1 ([Christensen et al., 1998](#)). Since effectively parameterized zonal models cannot  
2 produce the nonlinearities observed here, the base model is found to systematically  
3 overestimate regional stream-aquifer exchanges. This holds true for all levels of  
4 heterogeneity investigated here as controlled by CV.

5 The paper is organized as follows. In Section 2, the experimental framework used  
6 to model the MHRB and the stochastic methods used to produce locally  
7 heterogeneous hydraulic conductivity fields are described. Section 3 reports methods  
8 and results of investigations of H1 and H2. It presents results comparing simulations  
9 of stream-aquifer exchanges derived from (1) a base model whose effective  
10 conductivity parameters are specified by zone and (2) stochastic realizations of  
11 heterogeneous local-scale conductivity. Section 4 focuses on H3. The emergence of  
12 coherent slow paths in the flow fields is investigated as the source of the bias in base  
13 model estimates. Results are summarized and discussed in Section 5, and a few  
14 directions for future experiments are sketched.

15

## 16 **2. Experiment setting and model development**

17 The experimental approach is to compare alternative numerical models of  
18 hydrologic system dynamics that produce stream-aquifer exchanges in the Middle  
19 Heihe River Basin (MHRB), a closed basin in northwestern China of area of 8778  
20 km<sup>2</sup>. Stream-aquifer exchanges are estimated by (1) a so-called base model that  
21 specifies hydraulic conductivity on zonal scales and (2) a set of related models that  
22 incorporate local-scale heterogeneity in their parameterizations. Zonal conductivity in  
23 the base model is calibrated using the PEST parameter estimation tool ([Doherty et al.,](#)  
24 [1994; Sophocleous et al., 1999](#)), and the base model assigns the same calibrated value  
25 of hydraulic conductivity to every grid point in a given zone.

26 The level of heterogeneity of hydraulic conductivity is the experimental control  
27 variable in local-scale simulations. It is set by adding varying levels of randomness to  
28 the zonal values of the base model. The result is a random field of conductivities with

1 expected values that are the same in a given zone as the base model's effective  
2 conductivity. Otherwise, system parameters including specific yield and streambed  
3 conductance and boundary conditions are the same for all simulations. All  
4 computations are conducted using the MODFLOW simulation environment (Leake  
5 and Prudic, 1991; McDonald and Harbaugh, 2003; Rodríguez et al., 2006).

## 6 **2.1. Study area**

7 The MHRB is contained in the Heihe River Basin, the second largest closed river  
8 basin in China, which drains a total area of 142.9 thousand km<sup>2</sup>. The MHRB is in a  
9 semi-arid region with average annual rainfall of approximately 50-200mm/y, most of  
10 which occurs from May to October. The river originates in the Qilian Mountains of  
11 Qinghai Province and then flows through Gansu Province to western Inner Mongolia.  
12 The average annual inflow from mountain areas upstream is 1.58 billion m<sup>3</sup> as  
13 measured at the Yingluoxia Gauge (YLX), and the discharge through the Zhengyixia  
14 Gauge (ZYX) is 0.95 billion m<sup>3</sup>. The 184 km long reach from YLX to ZYX defines  
15 the MHRB study area (Fig. 1), which is known to be influenced by temporal patterns  
16 and spatial distributions of stream-aquifer exchanges (Zhou et al., 2011).

17 Intensive stream seepage and groundwater discharge occur in the study area along  
18 the river in fluvial and alluvial fans. The exchanges proceed in two directions:  
19 groundwater flows through the streambed into the stream (discharging gaining  
20 stream), and stream water infiltrates through the streambed into the groundwater  
21 system (leaking losing stream) which is the same as general states presented in  
22 (Winter, 1995; Kalbus et al., 2006). Groundwater discharge to streams maintains  
23 natural hydrologic systems during periods of low stream flow through base flow  
24 (Sophocleous et al., 1995; Hantush, 2005). Streams are an important source of  
25 groundwater recharge at higher elevations. Conjunctive use of surface and subsurface  
26 waters is a potentially important resource management tool in semi-arid regions like  
27 the Heihe River Basin whose potential also depends on system state estimates.

28 The Middle Heihe River leaks into a sandy fluvial area immediately after YLX  
29 and then enters an alluvial plain composed of fine soil. At that point substantial stream

1 seepage, diversion, and groundwater discharge (base flow) occur along the stream.  
2 The Middle Heihe River is a wide and shallow stream, and the area of the stream  
3 channel is much greater than the lateral areas of both banks. Thus the exchange of  
4 stream water and groundwater occurs primarily in the vertical direction. The plain of  
5 fine-grained soil along the river is the main area where springs and groundwater  
6 emerge. Thirty irrigation areas are distributed throughout the study area. Groundwater  
7 tables range from 0m to 300m beneath the land surface, and aquifer thickness varies  
8 from tens to a couple of hundred meters.

## 9 **2.2. Numerical model of stream-aquifer exchanges**

10 All stream-aquifer interactions are simulated using the numerical modeling tool  
11 MODFLOW with the stream package (STR) for one-dimensional stream flow and  
12 two-dimensional groundwater flow in this study. The stream package (Leake and  
13 Pradic, 1991) simulates stream flow with Manning's equation and interactions with  
14 groundwater flow using Richard's equation, which assumes vertical, gravity-driven  
15 flow and neglects capillarity. This is an acceptable assumption for the typical alluvial  
16 sediments of the kind found in the MHRB (Spanoudaki et al., 2009; Huang, 2012).

批注 [Jinfeng2]: We added this to  
make this sentence more accurate.

17 The stream and aquifer systems are coupled in the model through an iterative  
18 process in which convergence of state variables linking the two domains is used as the  
19 criterion for accepting a solution. The stream stage and groundwater table are iterated  
20 at each time step until the differences between two iterations are within a small  
21 tolerance. Seepage is calculated from the product of the head difference times a  
22 streambed conductance. In regional-scale groundwater models it is reasonable to  
23 assume a homogeneous low-conductivity streambed within a heterogeneous aquifer  
24 (Kalbus et al., 2009). Conductance is assigned based on an existing calibration and  
25 measured data values between 1-3 m/d (He and Zhao, 2007; Zhou et al., 2011).

批注 [Jinfeng3]: We changed  
"gradient" into "difference" here.

26 Since aquifer thickness is small compared to its horizontal dimensions, one layer  
27 is sufficient for the vertical discretization. Workman et al. (1997) pointed out that the  
28 discrete cell size can be 1-2km in regional groundwater flow models, as a river can  
29 affect water table elevations as far as 1525 m from the middle of the stream. Thus the

1 study domain is discretized into 155 rows and 172 columns, with each cell size 1km x  
2 1km. The aquifer is simulated as a free-surface boundary able to fluctuate in response  
3 to recharge from irrigation fields, evapotranspiration, flow to drains, and interaction  
4 with streams. The recharge package (RCH) is used to input rainfall and irrigation  
5 seepages as vertical boundaries, and the recharge distribution is set according to the  
6 data from [Hu et al. \(2007\)](#). The ETS package is employed to simulate phreatic  
7 evaporation considering the multiple-linear relationship with groundwater depth.  
8 Based on previous studies ([Zhou et al., 2011](#); [Tian et al., 2015](#)), spring flow is also  
9 calculated in irrigation areas by representing the drainage area as drain cells.

10 The groundwater table observed on January 1 of the year 2000 is input and  
11 interpolated as initial head for all simulations. The time step is 5 days, and the  
12 simulation period is one year. Stream inflow at the YLX Gauge and groundwater  
13 lateral recharges from mountain areas are used as an upper boundary, and outflow at  
14 the ZYX Gauge is taken as a lower boundary ([Zhou et al., 2011](#)). In the mountain  
15 front region, the aquifer has a high proportion of pebbles, sand and gravel, while the  
16 plain of the lower area is composed of thick unconsolidated alluvial fills with alluvial  
17 sand, silt, and clay ([Hu et al., 2007](#)).

### 18 **2.3. Base model**

19 Previous research has identified 16 major hydrologic zones within the MHRB  
20 based on variations of hydraulic conductivity and specific yield ([Hu et al., 2007](#); [Jia et](#)  
21 [al., 2009](#)). In this study, the PEST parameter estimation system is used to calibrate  
22 aquifer parameters (zonal horizontal conductivity  $K_z$  and specific yield  $S_z$ ) for the  
23 different zones,  $z = 1, \dots, 16$ . The parameterization of conductivity by constant  
24 effective values, one each for the 16 coarse zones, is the foundation of the base model.  
25 The 16 zonal conductivities are also used as expected values for the stochastic  
26 generation of locally refined conductivity fields as described in the next sub-section.

27 The objective function for PEST estimates is the sum of squared differences  
28 between observations and simulations of groundwater tables at 34 wells distributed  
29 through the basin. Effective parameters  $K_z$  and  $S_z$  are optimized and estimated

1 separately for the 16 zones of the domain due to computational limitations. The  
2 lower and upper levels of parameter settings for conductivity are 0.5~50 m/d and are  
3 0.01~0.25 for specific yield without considering anisotropy. The procedure of PEST  
4 includes an initial MODFLOW simulation, calculation of the Jacobian matrix for each  
5 parameter, and different Lambda upgrade. After the calibration of  $K_z$  values the  
6 specific yields of the system,  $S_z$ , are optimized with PEST for transient conditions by  
7 minimizing the groundwater table errors at observation wells.

#### 8 **2.4. Stochastic realization of conductivity fields**

9 Stochastic simulations are the basis for local-scale realizations of hydraulic  
10 conductivity fields,  $K(x)$ , used in comparisons. The variable  $x$  corresponds to a point  
11 in the 155 x 172 computational grid used in all simulations of hydrologic system  
12 dynamics in the MHRB. Local parameters  $K(x)$  are defined by log-normally  
13 distributed perturbations on the zonal conductivity field of the base model,

14 
$$\ln K(x) = Y(x) = Y_z + Y'(x), \quad Y'(x) \sim N(0, V_z) \text{ for all } x \in \text{zone } z. \quad (1)$$

15 The zonal mean,  $Y_z$ , and variance,  $V_z$ , are defined in terms of the base model  
16 parameters,  $K_z$ ,

17 
$$Y_z = \ln \frac{K_z}{\sqrt{1 + C}}, \quad V_z = \text{Var}[Y(x)] = \ln(1 + C), \quad x \in \text{zone } z \quad (2)$$

18 where  $C$  is the Coefficient of Variation (CV).

19 In order to compare the effects of different levels of total heterogeneity,  
20 realizations of conductivity fields are generated corresponding to six values  $C = 0.1,$   
21  $0.2, 0.5, 0.8, 1.0, 2.0$ . Grid-scale analyses at different levels of heterogeneity are based  
22 on a sample of 10 realizations of log-normally distributed random conductivity fields  
23 for each value of  $C$ . Local scale simulations of groundwater flow and stream-aquifer  
24 exchanges are produced using realizations of  $K$  fields based on Eqns. (1) and (2) in  
25 the general model.

26 Grid point values of conductivity are sampled independently, so no correlation  
27 structure is imposed on local conductivities. It is generally accepted that hydraulic

1 conductivity is a random field that is typically correlated over a continuous range of  
2 small scales, becoming uncorrelated once a characteristic correlation length is reached  
3 (Zhang, 2002; Rubin, 2003). The effect of small-scale correlations on regional  
4 velocities and mass transport is understood through second-order for spatially  
5 stationary conductivity fields (Gelhar and Axness, 1983; Winter et al., 1984; Neuman  
6 and Orr, 1993) and for a wider range of fields that are heterogeneous at local and  
7 regional scales (Winter and Tartakovsky, 2002). The small scale of our study is set  
8 by the 1 km x 1 km size of our grid cells. Since many alluvial systems have  
9 correlation lengths that are much less than that, e.g., Rehfeldt et al. (1992) and Riva et  
10 al. (2006), it is informative, and in some cases realistic, to investigate the effect that a  
11 field of locally independent, identically distributed conductivities has on the state  
12 variables of regional models. Indeed, our experiments show that stream-aquifer  
13 exchanges estimated by a typical regional simulation like the base case can be biased  
14 even when local conductivities are uncorrelated.

## 15 **2.5. Tests of Hypotheses**

16 Comparisons between simulations produced by the base model and local-scale  
17 models depend on either normalized squared departures between fluxes produced by  
18 the base model and the locally heterogeneous models or ratios between the same  
19 fluxes. The results of comparisons are said to support H1 and H2 if simulated values  
20 produced by the base model exhibit systematic bias with respect to local-scale  
21 simulations of stream-aquifer exchanges. H3 is evaluated by comparing normalized  
22 squared departures of groundwater fluxes produced by the base model with samples  
23 produced by locally resolved simulations.

## 24 **3. Simulated stream-aquifer exchanges**

25 This section focuses on H1 and H2, the hypotheses that simulations of exchanges  
26 of water between the stream and aquifer systems produced using locally  
27 heterogeneous conductivity fields are systematically less than estimates produced by  
28 the base model. Results are given separately for the base model and for models with

**批注 [Jinfeng4]:** We added a paragraph to response the comments about why it makes sense to study the influence of uncorrelated fields.

**批注 [Jinfeng5]:** This section 2.5 is separated since the topic (hypothesis testing) is different from the previous discussion.

1 parameterizations affected by local scales of heterogeneity and then compared.  
2 Levels of CV are manipulated as control parameters in the experiments. Simulated  
3 groundwater fluxes are used later (Section 4) to evaluate H3, the hypothesis that  
4 locally heterogeneous conductivity affects the emergence of preferential paths in the  
5 aquifer.

### 6 **3.1. Base model calibration and simulation results**

7 The lower fluvial plain of the MHRB is mainly composed of relatively low  
8 permeability silts and clay, while the upland aquifer, containing mostly sand mixed  
9 with gravel, is more permeable (Hu et al., 2007). This distribution is reflected in  
10 estimates of zonal conductivity and specific storage,  $K_z$  and  $S_z$ , derived from a PEST  
11 calibration based on a record of 5-day groundwater table variations in the year 2000  
12 (Fig. 1). The differences between well heights simulated using the PEST calibration  
13 and observations yield a residual mean of -0.19 m, standard error of 0.021 m, root  
14 mean square (RMS) of 1.4 m, and normalized RMS of 0.77%. The PEST calibration  
15 results specify higher conductivity for upstream areas near mountain fronts than for  
16 the lower fluvial plain in accord with the characteristic geology of the basin.

17 Simulated river stages and groundwater tables for June and December along the  
18 183km river distance are displayed in Fig. 2a and Fig. 2b. The groundwater table is  
19 generally much lower than the stream stage for about 25 km below Yingluoxia Gauge  
20 (YLX), indicating a losing reach of stream, as can be seen from these two figures. The  
21 groundwater table becomes quite shallow in the plain downstream of YLX, and the  
22 stream may be losing or gaining at different seasons and locations until the outlet at  
23 the Zhengyixia Gauge (ZYX).

24 River stage in June is relatively higher than that in December (Fig. 2c), as the  
25 stream flow is higher in flood season. Nevertheless, the groundwater table along the  
26 river in December is a bit higher because there is almost no pumping for irrigation in  
27 that month. Stream inflow from YLX exhibits clear seasonal variations within the  
28 year with a large pulse of water in Spring-Summer due to snowmelt (Fig. 2d). This  
29 effect is clearly reflected by monthly stream leakage to groundwater ( $\text{m}^2/\text{km/day}$ ). On

批注 [Jinfeng6]: We added the reference here.

批注 [Jinfeng7]: We added this to make it more clear.

1 the other hand, groundwater discharge to the river (or base flow) is relatively stable  
2 and less controlled by the seasonal inflow from station YLX.

3 The pattern of groundwater flow is not only controlled by the distribution of  
4 hydraulic conductivity, but also by the configuration of the water table. Magnitudes of  
5 average groundwater flow velocity are higher near the mountain fronts than in the  
6 lower plains (Fig. 3a). Average monthly stream leakage rates ( $\bar{Q}_b$ ), where the average  
7 is taken over all monthly values, exhibit critical transition points between upwelling  
8 and downwelling zones (Fig 3b). The stream is losing in deep groundwater areas near  
9 mountain fronts and becomes a gaining stream in the lower plain where groundwater  
10 tables are shallow.

11 The intensity of stream-aquifer interactions also varies seasonally. Interactions in  
12 summer and autumn show similar patterns with water exchanges of losing streams  
13 and gaining streams stronger than the monthly average. Stream inflow is higher and  
14 recharge to groundwater (precipitation and irrigation seepage) is relatively larger in  
15 these seasons. Thus, leakage from losing streams and groundwater discharge along  
16 gaining streams both become larger than the corresponding seasonal average. The  
17 magnitudes of water exchange are more spatially variable in the high-flow seasons of  
18 winter and spring: the magnitude augmentation (compared with seasonal average) of  
19 water exchanges for losing streams and gaining streams can be as large as 1041 and  
20 317  $\text{m}^2/\text{km/day}$  respectively. However, the water exchanges of the losing streams and  
21 gaining streams become much weaker in spring and winter, as the stream inflow from  
22 YLX is relatively low and the groundwater recharge (precipitation and irrigation  
23 seepage) is quite small.

### 24 **3.2. Influence of local heterogeneity on simulated results**

25 Groundwater simulations based on local (grid-scale) simulations of hydraulic  
26 conductivity  $K(x)$  display more spatially heterogeneous system states than the base  
27 model. Realizations of highly heterogeneous  $K(x)$  fields are produced by applying  
28 the method of Eqns. (1) and (2) in Section 2. Fig. 4 displays grid-scale perturbations  
29 of  $K(x)$  from the zonal mean  $K_z$  for coefficients of variation (CV) of magnitude  $C =$

1 0.1 and  $C = 2$ , as indicated by  $K(x)/K_z$ . Higher perturbations from zonal mean  
 2 conductivity occur for higher CV, which follows from the definition of zonal standard  
 3 deviation (Eqn. 2).

4 Grid-scale simulations,  $W_G(x)$ , of groundwater tables at the end of the simulation  
 5 period (Dec) are more variable than the base result,  $W_B(x)$ . Point-wise differences  
 6 between the two,  $\Delta W(x) = W_B(x) - W_G(x)$ , are about equally distributed between grid  
 7 cells where the grid-scale water table is higher than the base case ( $\Delta W(x) < 0$ ) and  
 8 lower ( $\Delta W(x) > 0$ ), although there is a slightly greater chance of a rise. The number  
 9 of cells where the absolute change in the water table is large ( $|\Delta W(x)| > 1$  m) increases  
 10 systematically with CV, and the number of cells where  $|\Delta W(x)| < 1$  m decreases  
 11 correspondingly. The point-wise differences exhibit a pattern of compact spatially  
 12 coherent areas where water tables consistently increase or decrease together. This is  
 13 despite the lack of any correlation in the values of grid-scale conductivity.

14 It is convenient to use an indicator,

$$15 I_m = Q_m / Q_m^{(B)} \quad (3)$$

16 to compare monthly stream-aquifer exchanges produced by local grid-scale models,  
 17  $Q_m$ , with monthly exchanges produced by the base model. Here  $m = 1, \dots, 12$   
 18 indicates the month.

19 The base model simulation,  $Q_m^{(B)}$ , of total water exchanged between the stream  
 20 and aquifer during month  $m$  summed over all  $x = 1, \dots, n$  grid cells along the stream is,

$$21 Q_m^{(B)} = \sum_{x=1}^n Q_m^{(B)}(x) \quad (4)$$

22 Similarly,  $Q_m$ , the mean total exchange for month  $m$  averaged across all  $r = 1, \dots, N_r$   
 23 ( $=10$ ) locally refined models is

$$24 Q_m^{(r)} = \sum_{x=1}^n Q_m^{(r)}(x) \text{ and } Q_m = \frac{1}{N_r} \sum_{r=1}^{N_r} Q_m^{(r)} . \quad (5)$$

25 The mean monthly value of the aquifer-stream discharge indicator is always less  
 26 than 1 for all values of CV: the base model produces discharge values that are

1 systematically larger than the locally heterogeneous models (Fig. 5). When two  
2 standard deviation confidence intervals are calculated for  $I_m$ , a few intervals  
3 corresponding to the smallest CVs include 1 for some months. In those cases  
4 small-scale heterogeneities increase discharge in some local areas and the overall  
5 effect of heterogeneity is reduced. When CV equals 0.1, the monthly aquifer-stream  
6 discharge is quite close to the base model value (i.e., the expected value) since  
7 perturbations around the expected values are small in that case. On the other hand,  
8 mean indicator values decrease to nearly 0.8 as CV increases from 0.1 to 2, and  
9 standard deviations continue to increase. As heterogeneity in local models increases,  
10 the monthly aquifer-stream discharge indicator decreases and uncertainty as measured  
11 by standard deviation increases. The discharge ratio also shows some seasonal  
12 patterns, with smaller effects of heterogeneity in high-flow months, such as August  
13 and September. Compared with other months, the aquifer-stream discharge quantity is  
14 larger and the uncertainty is less in these months.

15 The mean monthly value of the corresponding stream-aquifer leakage indicator is  
16 also less than 1 in most months, and the standard deviations show increasing trends  
17 with increasing CVs, but the relative magnitudes of leakage are less than those of  
18 discharge and are closer to the base model (Fig. 6). Taking CV equaling to 2 for  
19 example, the ranges of mean values for stream-aquifer leakage and discharge are  
20 respectively 0.97-0.99 and 0.81-0.93, and the respective ranges of standard deviations  
21 for stream-aquifer leakage and discharge are 0.004-0.013 and 0.020-0.044.

22 The entire Middle Heihe River includes upstream segments where the dominant  
23 exchange mechanism is leakage and downstream segments where discharge is  
24 dominant. To separate these two confounding classes of fluxes, spatial effects of  
25 heterogeneous conductivity are further investigated by calculating indicator values  
26 ( $Q_m/Q_m^{(B)}$ ) for four major sub-streams in the MHRB. Results for discharge and leakage  
27 are shown for all 10 realizations of conductivity for each value of CV (Figs. 7 and 8).  
28 Stream 1 is an upstream segment while Streams 2-4 comprise the main stem of the  
29 river in the alluvial plain. The indicator values are almost all less than 1 for average

1 monthly discharge from these four sub-streams (Fig. 7), corresponding to the  
2 relatively larger impact of conductivity heterogeneity on groundwater processes  
3 leading to discharge. Stream-aquifer leakage is larger than the corresponding base  
4 model in every sub-stream during at least some months (Fig. 8).

5 The stream-aquifer water exchanges of these four sub-streams respond  
6 differently to local heterogeneity, reflecting the different groundwater flow regimes of  
7 the different sub-regions. For example, Stream 1 is mainly a losing stream located in a  
8 mountain front area with a deep groundwater table, thus aquifer heterogeneity has a  
9 relatively small effect on stream-aquifer exchanges. Streams 2-4 go through the plain  
10 where water exchanges are affected by pumping and recharge schemes, and the  
11 differences between  $Q_m$  and  $Q_m^{(B)}$  are more obvious. Since groundwater depths are  
12 shallow and extensive stream-aquifer interactions occur in these areas, the effects of  
13 aquifer heterogeneity on water exchanges of these streams are relatively strong. The  
14 values of  $Q_m/Q_m^{(B)}$  are smaller during summer and autumn, when the stream inflow  
15 from YLX and precipitation are relatively large.

16

## 17 **4. Slow paths**

18 In this section evidence is presented for the hypothesis (H3) that the systematic  
19 bias observed in Section 3 is due to the response of groundwater flow to local  
20 heterogeneities in conductivity fields. Spatially coherent slow paths are seen to  
21 emerge in groundwater flows simulated in realizations of heterogeneous conductivity  
22 fields, and their density increases as the CV of experiments increases. This occurs  
23 despite the lack of any correlation in the spatial distribution of local-scale  
24 conductivity itself.

### 25 **4.1. Local scale conductivity field heterogeneity**

26 It is well-known that groundwater system parameters exhibit heterogeneity on  
27 multiple scales ranging down to the smallest (Neuman et al., 1987; Neuman, 1990,  
28 1994). Here the statistics of locally heterogeneous conductivity fields are analyzed

1 and compared to the mean fields corresponding to the calibrated conductivity  
2 parameters of the base model. A single realization is chosen at random from the 10  
3 available per level of CV, and its statistics are analyzed. Results for other  
4 realizations are essentially the same.

5 The point  $x$  is a grid cell in the  $z^{\text{th}}$  zone. The ratio

6 
$$\rho_z(x) = K(x)/K_z \quad (6)$$

7 compares  $K(x)$ , the local conductivity at  $x$  to  $K_z$ , the expected value of  $K(x)$  defined by  
8 the calibrated zonal conductivity parameterizing the base model. The summary  
9 statistics of  $\rho_z(x)$  describe the overall behavior of normalized local conductivity when  
10 adjusted for zone (Table 1). The arithmetic means of the  $\rho_z(x)$  equal 1 for all values of  
11 CV, implying that the conductivity field is indeed a realization drawn from an  
12 ensemble of fields whose zonal expected values are the base model values derived  
13 from the initial calibration. The standard deviations of the  $\rho_z(x)$  increase with CV.  
14 Both these behaviors are expected. Since hydraulic conductivity is bounded below by  
15 0, the ranges of minimum values are also limited; nonetheless, minimum values  
16 decrease by two orders of magnitude, which is consistent with the increase in CV.  
17 Maximum values increase with increasing CV. Calculations of Moran's I (not shown)  
18 indicate that values of  $K$  are not spatially correlated for any CV.

19 The geometric mean of  $\rho_z(x)$  declines from 0.96 to 0.76 as the heterogeneity of  
20 the conductivity field (CV) increases. Since the effective conductivity of a  
21 heterogeneous 2D field is equal to its geometric mean (Matheron, 1967; Gutjahr et al.,  
22 1978), groundwater flow is expected to be slower in more heterogeneous fields where  
23 CV is higher. A related effect is observed in the simulations of aquifer-stream  
24 discharge reported in Section 3.2 where both overall discharge and discharge in  
25 individual stream segments (Fig. 5 and Fig. 7) decline as CV increases. This is further  
26 suggested by the trend in the percentage of grid cells with  $K(x)$  values less than  $K_z$  (i.e.  
27  $\rho_z(x) < 1$ ) which increase from 54.8% to 64.2% with CV increasing from 0.1 to 2. It

1 should be noted that the median value also shows a decreasing trend from 0.99 to  
2 0.84.

3 These trends are evident in grid-scale  $K(x)$  field comparison maps based on the  
4 realization used to construct Table 1 (Fig. 9). Maps for other realizations are similar.  
5 Black grid cells are locations where  $K(x) < K_z$ , while white grid cells have values  
6  $K(x) > K_z$ . The number of black grids clearly increases with heterogeneity (CV),  
7 illustrating the increasing percentage of area occupied by locations with smaller  
8 conductivity than expected.

9 **4.2. Emergence of slow paths**

10 To evaluate hypothesis H3, we compare groundwater fluxes  $q(x)$  and  $q_b(x)$  obtained  
11 respectively from (i) the flow simulation based on the same realization of a locally  
12 heterogeneous conductivity field,  $K(x)$ , that was selected in Section 4.1 and (ii) the  
13 simulation based on the calibrated base model field,  $K_z$ . We adopt the normalized  
14 difference

$$15 \Delta q(x) = (q(x) - q_b(x)) / \sqrt{q(x) \bullet q_b(x)} \quad (7)$$

16

17 to indicate differences between flow simulations. Here  $\Delta q(x) < 0$  indicates a point  
18 where flow due to local variations of conductivity,  $q(x)$ , is less than flow due to the  
19 base model,  $q_b(x)$ . The normalization removes large-scale effects due to zonal  
20 averages from the analysis.

21 Summary statistics of flow (Table 2) support the hypothesis that locally  
22 heterogeneous conductivity fields induce reduced overall flows even though the  
23 heterogeneous conductivities are spatially independent. The arithmetic mean  
24 difference drops from -0.05 to -0.51 as CV increases from 0.1 to 2, and the median  
25 and minimum values exhibit a declining trend as well, implying that groundwater  
26 flow estimated by the local-scale model is slower at most points than the groundwater  
27 flow estimates from the base model. Meanwhile, standard deviations steadily  
28 increase from 0.175 to 0.833, indicating that groundwater flow becomes more  
29 variable as CV increases. Additionally the percent of area that is occupied by

1 relatively lower groundwater flow ( $q(x) < q_b(x)$ ) increases with increasing  
2 heterogeneity.

3 This fact is amplified by examining the spatial distribution of normalized  
4 differences  $\Delta q(x)$  (Fig. 10). Other realizations exhibit similar patterns. Black grid  
5 cells correspond to locations where  $\Delta q(x) < 0$ , while white grid cells are points where  
6  $\Delta q(x) > 0$ . As aquifer heterogeneity increases, the area covered by black grid cells  
7 expands, consistent with the last line of Table 2. This is somewhat more pronounced  
8 in low-lying regions where zonal mean hydraulic conductivities are low (cf. Fig. 1).

9 The distribution of locations where  $\Delta q(x) > 0$  ( $\Delta q(x) < 0$ ) is fairly uniform in the  
10 simulation with relatively low heterogeneity ( $CV = 0.1$ ). Areas in zone 1 where there  
11 seems to be a slightly higher concentration of  $\Delta q(x) < 0$  may be exceptional. It should  
12 also be noted that relatively strong local anisotropies in the direction of the stream  
13 appear throughout the basin, except in zone 1. The relatively uniform spatial  
14 distribution of the  $\Delta q(x)$  index begins to disappear as  $CV$  increases. When  
15 heterogeneity is high ( $CV = 1.0, 2.0$ ), areas where the  $\Delta q(x)$  index is less than zero  
16 generally coincide with zones of low conductivity (like zones 1, 2, 3, etc. in Fig. 1).  
17 Zones of high conductivity are somewhat harder to pick out, but there are obvious  
18 areas where  $\Delta q(x) > 0$  that correspond to areas of high zonal conductivity (like zones  
19 10, 8, 9, etc. in Fig. 1).

20 Coherent areas of relatively high and low flow build up in the groundwater  
21 simulations (Fig. 10), especially at high levels of heterogeneity (high  $CV$ ). This seems  
22 related to the increase of the area occupied by points of low conductivity with  
23 increasing heterogeneity (Table 1). Yet points of relatively low conductivity do not  
24 exhibit spatial coherence (cf. Fig. 9), nor should they since the random perturbation to  
25 conductivity that is added at any given point is chosen independently of all other  
26 points. The spatial coherence of low flux areas, as measured by  $\Delta q(x) < 0$ , results  
27 from the cumulative effect on continuous flows of blockages arising from spatially  
28 independent low conductivities. The flow paths of other simulations are statistically  
29 the same as this one, although their actual locations and geometry are different.

1    **5. Summary and Concluding Remarks**

2    This study focuses on three related hypotheses about the effects of locally  
3    variable hydraulic conductivity fields on regional exchanges of water between streams  
4    and aquifers: (H1) small-scale heterogeneities of hydraulic conductivity significantly  
5    affect simulated stream-aquifer water exchanges in river basins, and hence,  
6    computational projections of them; (H2) systematic biases arise in estimates of  
7    exchanges if small-scale heterogeneities are smoothed by aggregation into a few  
8    sub-regions; and (H3) the biases result from slow-paths in groundwater flow that  
9    emerge due to small-scale heterogeneities.

10    The study addresses these hypotheses through computational experiments by  
11    simulating system states of the hydrologic systems of the Middle Heihe River Basin  
12    (MHRB) of northern China. The study compares (i) estimates of stream-aquifer  
13    exchanges and groundwater fluxes produced by a base model that reflects current  
14    practice of parameterizing hydraulic conductivity on sub-regional scales to (ii)  
15    estimates produced by a related set of models whose conductivity parameters are  
16    spatially heterogeneous on local (grid-point) scales. The computational experiments  
17    provide evidence that regional system states, specifically exchanges of water between  
18    the MHRB's streams and aquifers, respond significantly to local variations of  
19    conductivity.

20    Local-scale heterogeneities in conductivity fields cannot be resolved by effective  
21    zonal parameterizations used in the base model. The cumulative effects of local  
22    heterogeneities combine to produce spatially coherent "slow paths" in the resulting  
23    simulations of groundwater flows. Flow paths in locally heterogeneous systems  
24    appear to intersect enough relatively low conductivity areas compared to the base  
25    model to reduce groundwater flow regardless of zone. The systematic behavior  
26    observed in the local-scale experiments is also consistent with theoretical results of  
27    [Matheron \(1967\)](#) and [Gutjahr et al. \(1978\)](#).

28    The aquifer-stream discharge response is stronger than the response of  
29    stream-aquifer leakage. That may result from discharge's greater sensitivity to

1 variations of hydraulic conductivity in the MHRB. Stream segments that are further  
2 downstream are also more affected by heterogeneity than upstream segments. This  
3 seems consistent with the overall pattern of leakage in the Heihe River Basin where  
4 recharge occurs primarily in upland reaches that are not directly connected to the  
5 water table and average conductivities are relatively high, and thus are relatively  
6 unaffected by variations in conductivity.

7 The results presented here strongly suggest that local-scale variations in the  
8 conductivity system parameter are not averaged out as scales of representation  
9 increase, but instead significantly affect regional exchanges of water between streams  
10 and aquifers (H1): in these experiments local heterogeneity has non-linear effects on  
11 states of the regional system. That is so even when the level of heterogeneity in  
12 conductivity is fairly small, as measured by the coefficient of variation of the  
13 simulated conductivity fields (CV). These effects increase with CV. This is especially  
14 true of discharge, which the sub-regionally scaled base model systematically  
15 over-estimates (H2). The emergence of slow paths in the groundwater flow field (H3)  
16 appears to be the source of the non-linearities.

17 These non-linear effects have implications for water resources management in  
18 addition to their intrinsic scientific interest. Since the introduction of computational  
19 tools capable of approximating the dynamics of basin-scale hydrologic systems, it has  
20 become common to use effectively (zonally) parameterized coupled models to  
21 manage regional water resources (Chen and Shu, 2006; Werner et al., 2006; Dragoni  
22 et al., 2013). Although estimates of system states produced by such aggregated  
23 models have been assumed to approximate watershed dynamics up to reasonable  
24 amounts of unsystematic random error, this assumption is generally not tested. The  
25 base model used here, and the methods used to produce it, is typical of such zonally  
26 parameterized models. It has been an open question whether zonal parameterizations  
27 can produce estimates of system states that account for the effects of local-scale  
28 heterogeneity that are known to exist in parameters (Schmidt et al., 2006; Rodríguez  
29 et al., 2013). The results of this study reveal a systematic bias in approximations of  
30 stream-aquifer exchanges in the MHRB produced by the base model. This is

1 especially true of discharge. Similar effects have been observed in other studies  
2 ([Kalbus et al., 2009; Kurtz et al., 2013; Mendoza et al., 2015; Lackey et al., 2015](#)).

3 Most of the evidence for (or against) hypotheses like H1-3 will continue to be  
4 computational. Several additional lines of investigation suggest themselves  
5 immediately. First is the extension of this kind of study to other basins, both natural  
6 and synthetic. Extensions to three dimensions may be required in some cases. The  
7 respective roles of zonal and local heterogeneity can be investigated explicitly by  
8 applying Analysis of Variance ([Winter et al., 2006](#)), or other multivariate statistical  
9 techniques.

10 Local-scale heterogeneities are independent in this study. This is a weak  
11 assumption in the sense that it places a minimal number of restrictions on the spatial  
12 structure of conductivity fields, but its influence on conclusions about H1-3 is unclear.  
13 Hydraulic conductivity fields are generally correlated, so experiments that evaluate  
14 the effects of different levels and kinds of correlation should be pursued. Synthetic  
15 conductivity fields that reproduce specified correlation structures can provide large  
16 numbers of realizations of parameter fields with given values of control variables like  
17 correlation length and spatial anisotropy.

18 Finally, the existence of slow paths in groundwater flows, is inferred indirectly  
19 here from summary statistics (cf. the last line in Table 2) or by qualitative  
20 interpretations of results (Fig. 10). A Langrangian analysis based on particle  
21 tracking would allow the interaction between variations in conductivity and  
22 groundwater fluxes to be quantified more directly.

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3

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批注 [Jinfeng13]: New reference added.

批注 [Jinfeng14]: New reference added.

1

2 **Tables**

3

4 Table 1 Grid-scale  $K$  field statistics

$\rho_z = K(x)/K_z$	CV=0.1	CV=0.5	CV=1	CV=2
Arithmetic mean	1	1	1	1
Standard deviation	0.3	0.65	0.98	1.12
Min	0.2	0.04	0.024	0.006
Max	4.1	14.62	37.47	21.64
Median	0.99	0.942	0.89	0.84
Geometric mean	0.96	0.85	0.78	0.76
Percent of $K(x)/K_z < 1$	54.8%	59.0%	62.0%	64.2%

5 Table 2 Groundwater flow field statistics with local heterogeneity

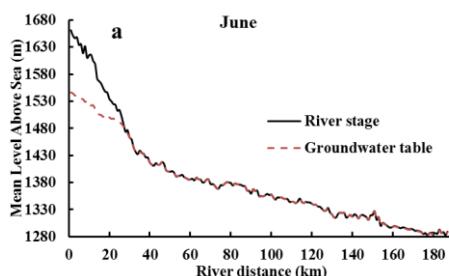
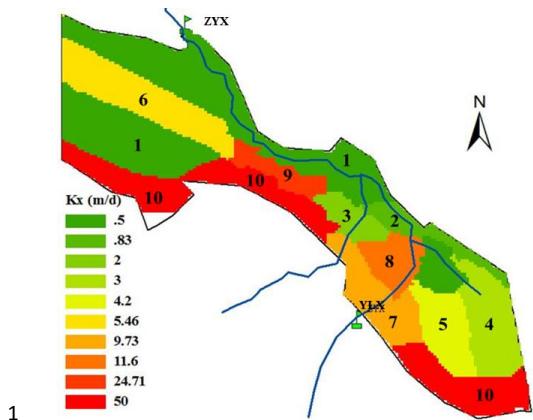
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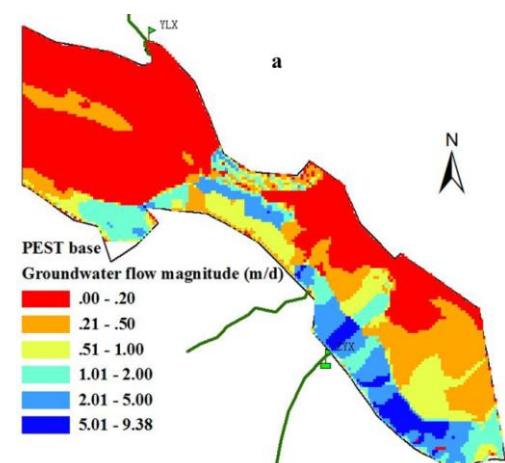
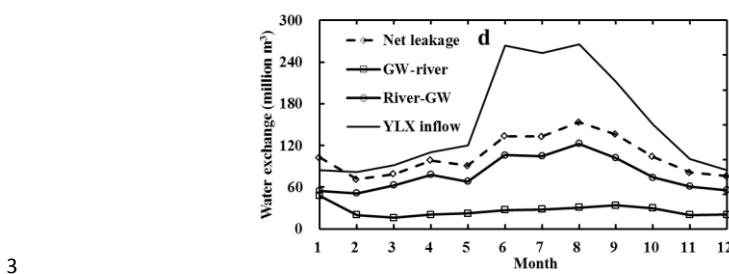
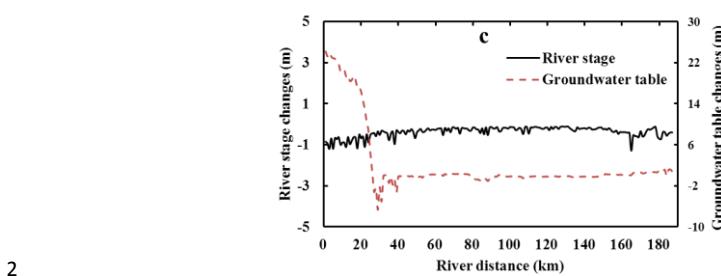
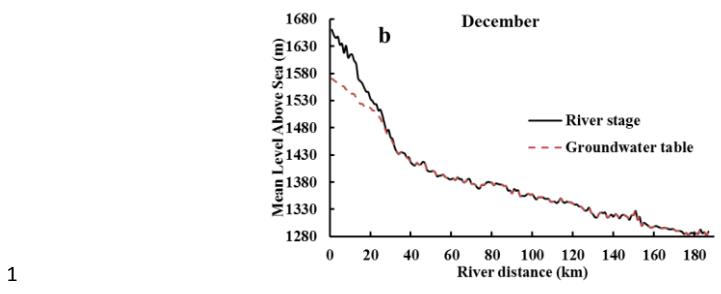
$\Delta q(x)$	CV=0.1	CV=0.5	CV=1	CV=2
Arithmetic mean	-0.05	-0.21	-0.34	-0.51
Standard deviation	0.175	0.398	0.569	0.833
Min	-1.833	-3.338	-4.901	-12.4
Max	1.54	1.429	3.458	2.721
Median	-0.017	-0.075	-0.14	-0.234
Percent of $q(x) < q_b(x)$	61.9%	71.0%	75.5%	79.5%

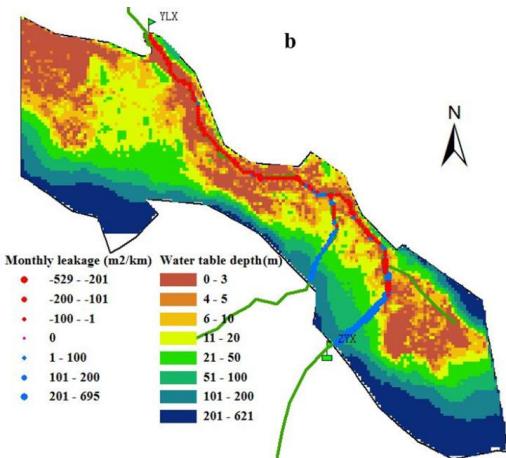
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8 **Figures**

9







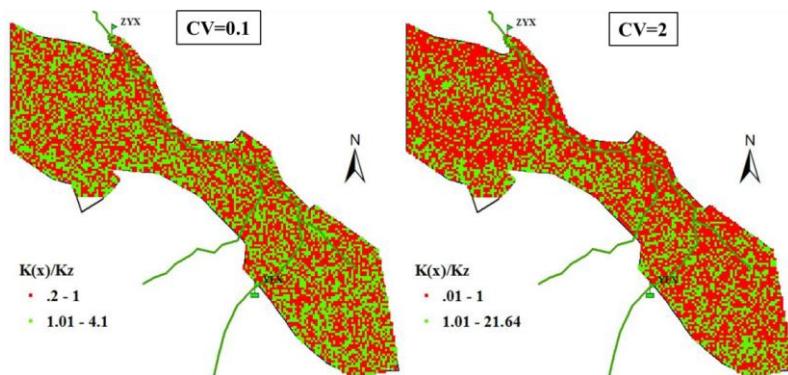
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2 Fig. 3. Groundwater flow rate  $q_0$  distribution (a); Average monthly leakage rate  $\bar{Q}_b$  and groundwater

3 table depth (b)

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5



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7 Fig. 4. Grid-scale realization of  $K$  field perturbation when  $CV$  equals 0.1 and 2

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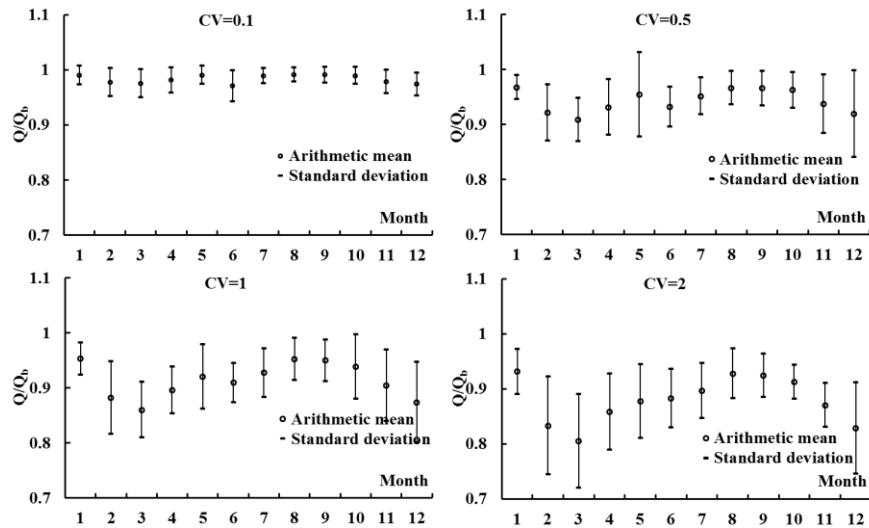


Fig. 5. Means and confidence intervals of aquifer-stream discharge from local model

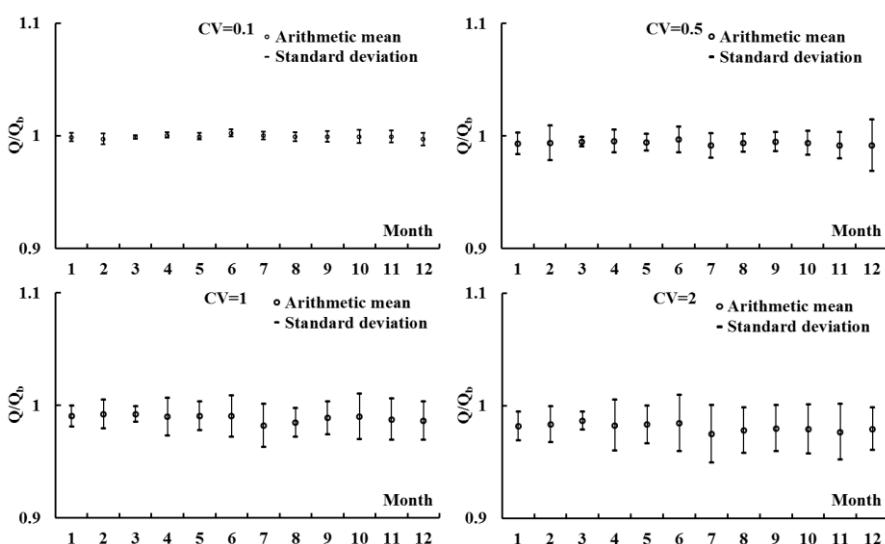


Fig. 6. Means and confidence intervals of stream-aquifer leakage from local model

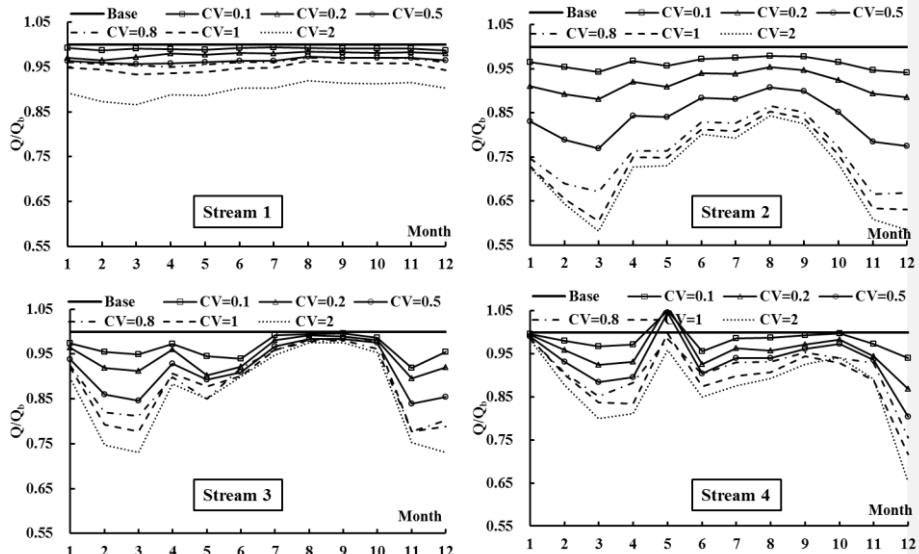


Fig. 7. Aquifer-stream discharges of different streams from refined model

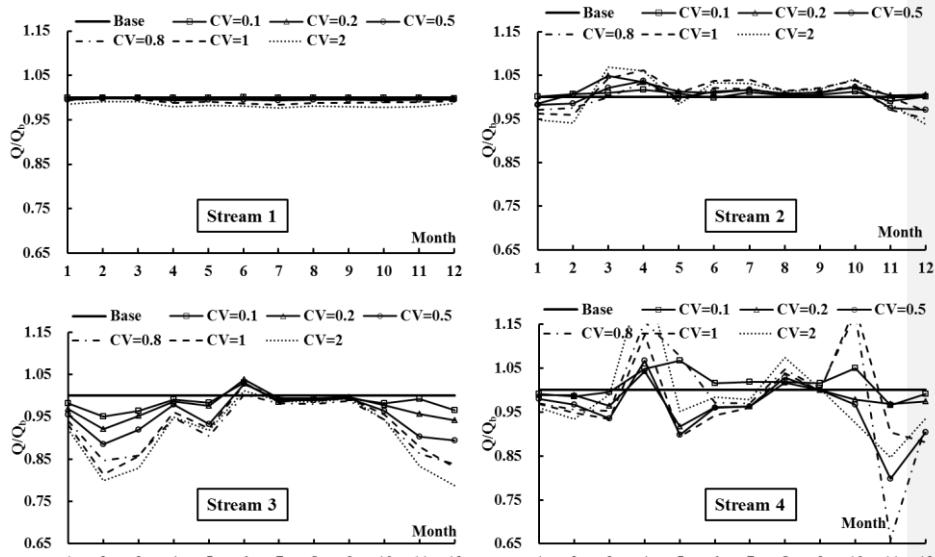
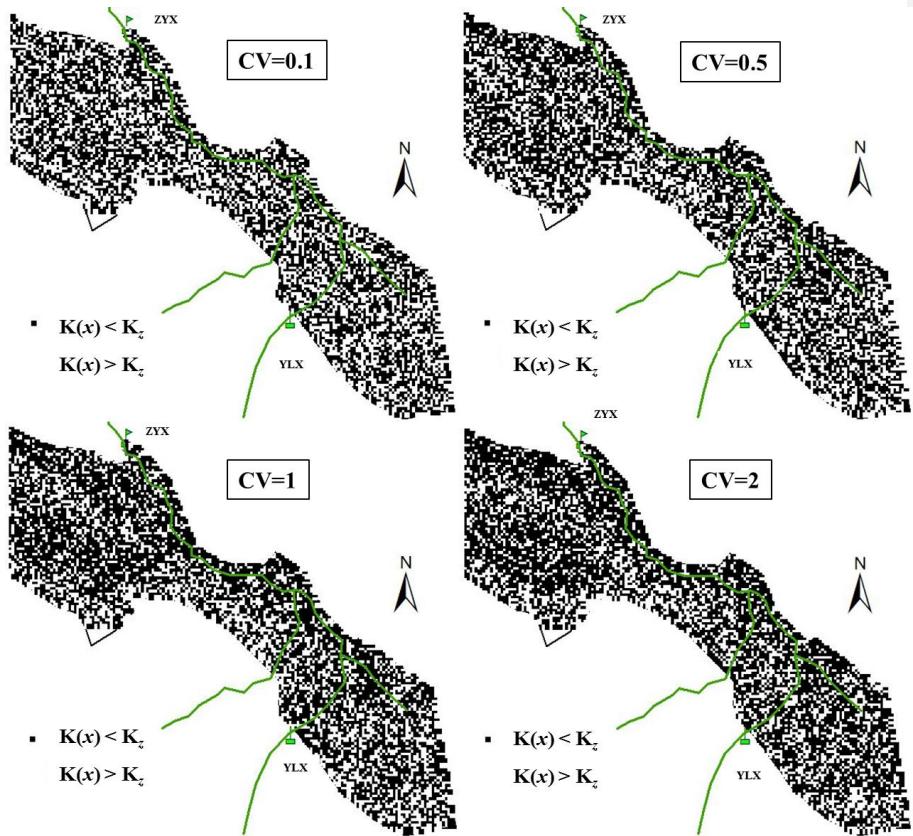
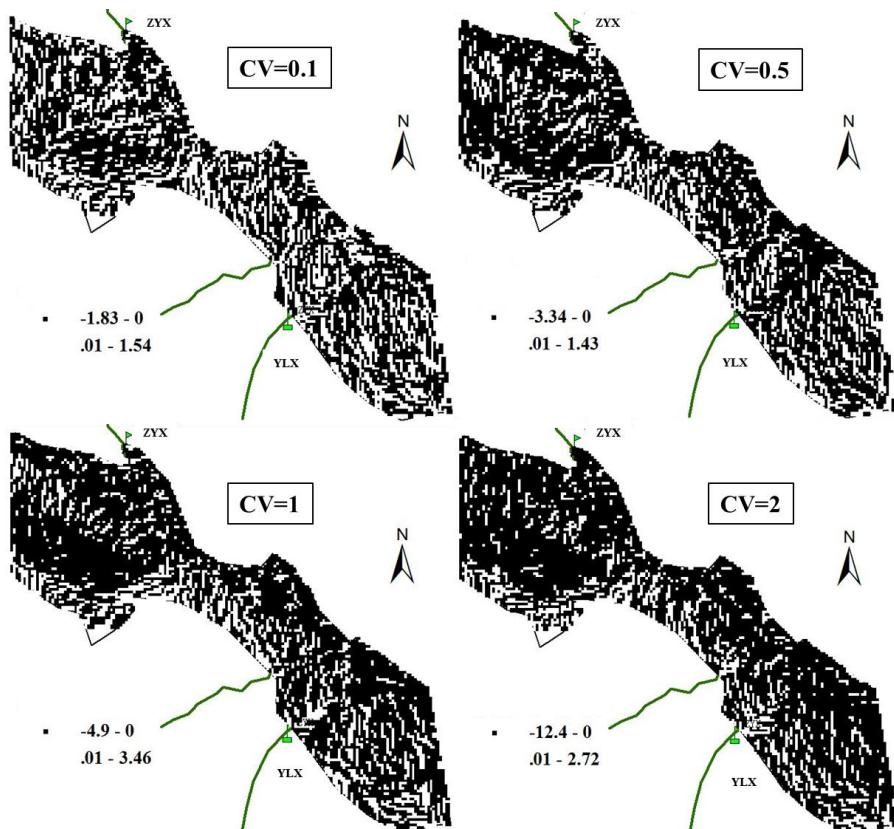


Fig. 8. Stream-aquifer leakages of different streams from refined model



1  
2 Fig. 9. Grid-scale  $K(x)$  field map for CV equaling to 0.1, 0.5, 1 and 2  
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1  
2 Fig. 10. The field of normalized groundwater flow differences  $\Delta q(x)$  with grid-scale  $K(x)$

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