

1 *General Response*

2 *Thank Prof. Sadegh very much for your careful review and kindly comments. We take*
3 *your comments into account seriously and will do the revision for our manuscript accordingly*
4 *which include: First, we will add some reference papers recommend in your comments.*
5 *Second, we will redesign our calibration experiment using multi measures of agreement*
6 *(RMSE, RMSEln, NSEln and NSE) instead of the single value of NSE (see the response to*
7 *comments of Prof. Zappa). Last but not least, we will check the writing carefully to correct*
8 *some writing mistakes. Replies to each detail comment are as below:*

9 **1. I would see this study as a step-wise calibration rather than diagnostic calibration.**

10 **In diagnostic calibration (diagnostic model evaluation, I would prefer to use), as**
11 **introduced by Gupta et al. (2008) signatures of the system (data) are used instead of**
12 **an ad hoc residual based likelihood (model evaluation) function. In this study a NSE**
13 **measure was used for step-wise calibration of each parameter which doesn't**
14 **correspond to the original term of "diagnostic model evaluation". Also when the**
15 **term diagnostic is used, reader would expect to see it points out some kind of**
16 **model/data error, while this study doesn't pin point which part of the model needs**
17 **correction/modification.**

18 *Thanks for this comment. The calibration method proposed in this study is a step-wise*
19 *calibration. However, each calibration step is based on a signature extracted from*
20 *hydrograph. Through analyzing the spatial-temporal dynamic of temperature, precipitation*
21 *data and snow/ice coverage, we extracted hydrological meaningful information from the*
22 *available data and developed four signatures: groundwater baseflow hydrograph partition,*
23 *snowmelt hydrograph partition, glacier melt hydrograph partition and rainfall direct runoff*
24 *hydrograph partition. Each signature was related to independent model components.*
25 *Parameters were estimated on the difference between the observed and simulated partitions.*
26 *To quantify the difference, the measure of agreement was used as function (a similar*
27 *procedure can be found by Hingray et al.(2010)). Our procedure works within the framework*
28 *of diagnostic problem proposed by Gupta et al. (2008): Diagnostic evaluation consists of*
29 *noting the behavioral (signature) similarities and differences between the system data D^{obs}*
30 *and the model simulations D^{sim} , and correction procedures by relating these to relevant model*

31 *components. The proposed calibration method aims at the diagnostic evaluation problem, i.e.*
32 *to determine those components of the model, which, when assumed to be functioning properly,*
33 *will explain the discrepancy between the computed and observed system behavior (Reiter,*
34 *1987;Gupta et al., 2008). The model components in this study consists of groundwater*
35 *baseflow, snow/glacier melt and rainfall direct runoff. To evaluate the model, the effects of*
36 *each component on simulation runoff were separated by hydrograph partitioning. The degree*
37 *of a realistic representation of each component achieved by the model was evaluated on each*
38 *calibration step. The proposed method can used to diagnose model structure and this can be*
39 *left for further study, but not included in the current study.*

40

41 **2. Introduction doesn't connect to the body of paper. In the introduction section**
42 **authors present a literature review of diagnostic model evaluation studies using**
43 **several indices (signatures) of the watersheds and in the current study they just use**
44 **NSE!**

45 *In this study, we extracted hydrological information from available data and partitioned*
46 *the hydrograph pertaining to water source for runoff generation. Partitions were developed*
47 *as signatures for model calibration and can be used for model component diagnostic (see the*
48 *above reply to comment 1). And we will redesign the calibration experiment using different*
49 *objective function to quantify the difference between the observed and simulated partitions in*
50 *each step here. The proposed method aims at the model diagnostic problem in an alpine area,*
51 *so a literature review of diagnostic model evaluation studies using several indices of*
52 *watersheds was presented in the introduction section.*

53

54 **3. Recently a formal statistical framework for diagnostic model evaluation is**
55 **introduced in the literature. Authors can include the following papers (amongst all)**
56 **to give readers a better overview of diagnostic model evaluation literature: Olden, J.**
57 **D. and Poff, N. L. (2003), Redundancy and the choice of hydrologic indices for**
58 **characterizing streamflow regimes. River Res. Applic., 19: 101–121. doi:**
59 **10.1002/rra.700 Vrugt, J. A., and M. Sadegh (2013), Toward diagnostic model**
60 **calibration and evaluation: Approximate Bayesian computation, Water Resour. Res.,**

61 **49, 4335–4345, doi:10.1002/wrcr.20354. Sadegh, M. and Vrugt, J. A.: Bridging the**
62 **gap between GLUE and formal statistical approaches: approximate Bayesian**
63 **computation, Hydrol. Earth Syst. Sci., 17, 4831-4850, doi:10.5194/hess-17-4831-2013,**
64 **2013. Several step-wise CRR model calibration papers also exist in the literature**
65 **than should be referred to in the paper.**

66 *Thanks. We will add some of these references directly relevant in the Sect. 1.1.*

67
68 **4. Fig. 2: In some months like April and June, temperature estimated from equation 1**
69 **(based on temperature lapse rate) nicely follow the fluctuations of observed**
70 **temperature while in others like February and November it fails to simulate the**
71 **temperature dynamics. How do you explain this phenomenon?**

72 *The temperature lapse rate was estimated based on temperature series in THS station*
73 *and two automatic weather stations (XT AWS and TG AWS) in the Tailan basin. While the*
74 *validation of the lapse rates shown in Fig.2 was carried out on the BT AWS in Kumalak basin.*
75 *The monthly relationship between temperature and elevation can be slight different in*
76 *different basins in Northwest China according to Zhang et al. (2012). This can explain the*
77 *different performance of the lapse rate in different months. Two points can be derived from*
78 *Fig.2.: the trend of temperature varies with elevation can be captured using the estimated*
79 *lapse rates, especially in the hot months (April to August) when snow/ice melt mainly occur;*
80 *the monthly lapse rates performed better than the annual constant lapse rate.*

81
82 **5. What explains the significant temperature lapse rate difference in different months**
83 **(-0.36 to -0.86)? In the most basic form, this lapse rate is a constant number for the**
84 **whole year.**

85 *The difference between monthly temperature lapse rates should be attributed to the*
86 *seasonal variation of air flow and prevailing wind direction in the mountain areas, while it is*
87 *still not very clear. However, many studies have pointed out the importance of considering*
88 *the monthly varied temperature lapse rate in melt simulation in the alpine areas (Aizen et al.,*
89 *2000; Zhang et al., 2012; Ji et al., 2013). According to Zhang et al. (2012), the mean monthly*
90 *temperature lapse rate in northwest China can vary from -0.29 to -0.7 °C/100m. The lapse*

91 rates used in this study was estimated according to temperature data series gauged in
 92 weather stations in the basin. Fig.2. shows that monthly lapse rate perform better than a
 93 constant number for the whole year in capturing temperature spatial distribution.

94

95 **6. Your objective function for estimating the lapse rate needs an “abs” function**
 96 **(absolute value), otherwise negative and positive residuals will cancel out. This**
 97 **might explain why we don’t see a good fit to measured temperature in some months?**

98 *Yes, thank you very much. There is a mistake of the objective function in Eqn. (2) which*
 99 *should be corrected as below:*

100
$$Z = \text{Min}[\sum (T_i - (T_{oi} + T_p \cdot (H - h)))^2]$$

101 **7. Suggestion: Fig 5a and 5b can be presented as subplots in one plot.**

102 *Thanks, we agree this, and the Figure will be modified (Figure1).*

103

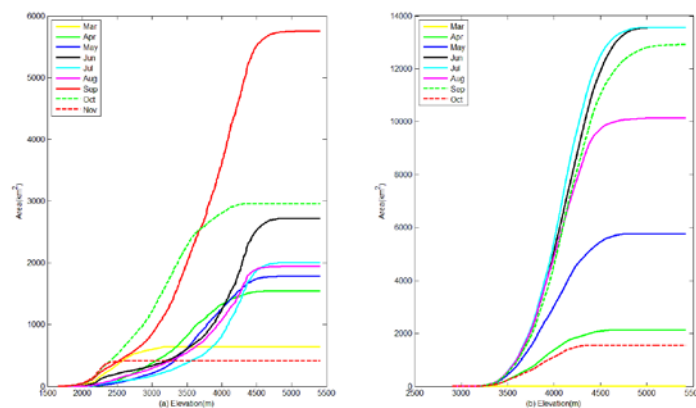
104 **8. Months names in Fig 5a legend are not in order! Is it just a typo?**

105 *The month names will be reordered, thanks.*

106

107 **9. I expected to see all the curves in Fig 5a-b continue to a common elevation (_5000),**
 108 **although might be horizontal at the end. Your study area does not change with**
 109 **month, just the melt area changes which can be represented by a horizontal line at**
 110 **higher elevations.**

111 *Yes, the curves will be extended to higher than 5000m, where melt areas are constant.*



112

113 *Figure1. (a) Cumulative monthly snowmelt area distribution by elevation for 2003 to 2012. (b)*
 114 *Cumulative monthly glacier melt area distribution by elevation for 2003 to 2012. The*

115 *snowmelt areas in December, January and February and the glacier melt areas in November,*
116 *December, January and February are zero and are not shown in this figure.*

117

118 **10. You should evaluate your model as a complete package for the evaluation period**
119 **and don't partition the hydrograph into several constituents. Eventually, your model**
120 **parts should work as a whole. Also in principle you don't know what type of process**
121 **generates your surface runoff in the evaluation period, so it doesn't make sense to**
122 **partition your hydrograph.**

123 *We evaluated the model for the whole simulation period eventually. As parameters were*
124 *identified based on different hydrograph partitions, we evaluated the simulation of each*
125 *partition firstly. And finally, the complete simulation in the evaluation period was composed*
126 *of different partition simulation. As described in Sect.2.1, the runoff concentration time in*
127 *TRB is less than 1 day, we can then separate the runoff components that generate surface*
128 *runoff in a step-wise way: in the SM period, both glacier melt and rainfall runoff don't occur,*
129 *so surface runoff in this period is generated by snowmelt alone; in the SM+GM period,*
130 *rainfall runoff doesn't occur, surface runoff is generated by snow and glacier melt; in the*
131 *SM+GM+R period, surface runoff is generated by both snow/glacier melt and rainfall. We*
132 *partitioned the hydrograph according to the runoff components, and estimated parameters*
133 *through evaluating the simulation of each partition.*

134

135 **11. Page 1273, line 18-21: It is mentioned that results of this study is comparable to an**
136 **automatic calibration method. If so, why do we need to partition the hydrograph?**
137 **And what has been diagnosed in this study?**

138 *The automatic calibration method used here is a benchmark method which uses the*
139 *single whole hydrograph as a measurement to evaluate all of the model parameters. The*
140 *comparison between the proposed and automatic method is to demonstrate the difference*
141 *calibration efficiency by using partitioned hydrograph and the whole hydrograph respectively.*
142 *Although the results between the two methods are similar, the proposed calibration method*
143 *has some good features: one is to reduce the parameter uncertainty during the calibration*
144 *procedure. Another is to diagnose model components through parameter calibration. In the*

145 *proposed calibration, we firstly extract hydrological information from available data to*
146 *separate runoff components in the hydrograph. Then we relate model parameter group to*
147 *each hydrograph partition. Each parameter group was calibrated upon the corresponding*
148 *runoff component separately, uncertainty from equifinality can be reduced in this way, while*
149 *the automatic calibration method does not have this function. During the calibration*
150 *procedure, we can diagnostically identify the components/processes which should be*
151 *improved to account for the under/over estimation. In this way, the efficiency of the*
152 *calibration procedure can be improved.*

153

154 **12. Table 5: for the evaluation period, we see a better performance for automatic**
155 **calibration rather than step-wise calibration! How do you explain this? And why**
156 **would a researcher leave automatic calibration for step-wise calibration?**

157 *Results in Table 5 show that the partitioned calibration method has a better performance*
158 *than the automatic method. In the revised manuscript, we will do a new comparison between*
159 *the proposed and the automatic calibration method using a benchmark model and seasonal*
160 *runoff simulations (see also reply to comments of Prof. Schaepli and Prof. Zappa). Thanks.*

161

162 **13. Page 1274, lines 1&2: “number of criteria handled by an automatic calibration**
163 **procedure should be lower than 5 : 1”! Number of evaluation criteria is not**
164 **important, the amount of information that they extract from data is more**
165 **important.**

166 *Thanks. Information extracted from data is also one kind of criteria. To calibrate model*
167 *parameters, hydrological meaning information can be used as criteria for measure of*
168 *agreement as done in the proposed calibration method in this study. The most significant*
169 *difference between the proposed and the automatic calibration method used here is that the*
170 *amount of information that they extract from data is different. In the automatic method, we*
171 *just used the single whole hydrograph to evaluate parameter groups, and no more*
172 *information had been extracted. It is may weak at constraining more additional criteria such*
173 *as simulation error of snow and glacier melt. Parameter uncertainty can be reduced by*
174 *constraining multi-criteria, while, the automatic calibration method can usually not handle*

175 *more than five criteria. The comparison between automatic and the proposed method shows*
176 *that the proposed method can expand the amount of information extracted from data and use*
177 *to constrain parameters. The number of model parameter and evaluation criteria can be*
178 *matched well in the proposed method, which is weak in the automatic method. When number*
179 *of calibrated parameter is increased, the proposed method should perform much better than*
180 *automatic method, which is however left for future study.*

181

182 **14. Page 1274, lines 9-12: It is mentioned that automatic calibration methods are**
183 **sensitive to the calibration data period while step-wise calibration is not. Different**
184 **calibration periods provide different events and might affect step-wise calibration in**
185 **the same way it affects automatic calibration. Actually it does affect step-wise**
186 **calibration as well. In the cross validation step (same page lines 19-21) it is shown**
187 **that the value of parameter B changes from 0.2 to 0.8 due to different calibration**
188 **events.**

189 *The proposed calibration method should be sensitive to calibration data in some degree,*
190 *but should be less than the automatic method. The cross validation results show that only the*
191 *value of parameter B varies significantly due to much higher peak flow in the late evaluation*
192 *period (2008-2012). Peak flows are mainly generated by storm-rainfall. Rainfall data series*
193 *is one of the main factors that influence the simulation of peak flows. The significant variation*
194 *of parameter B should be attributed to the error of rainfall input data. In the proposed*
195 *step-wise calibration method, data time series are not used for calibration directly.*
196 *Information of hydrological processes is extracted firstly and used to partition hydrograph.*
197 *The calibration data in the proposed method is not simple discharge series, but hydrograph*
198 *partitions which relates to the hydrological process physically. The relationship between*
199 *parameter and corresponding hydrological process is distinguished, and each parameter is*
200 *determined by the hydrology process it controls separately. The role of parameter on*
201 *discharge simulation is separated in the proposed method, calibration data in this method is*
202 *more hydrological meaningful than simple data time series usually used in the automatic*
203 *methods.*

204

205 **15. Page 1275, line 11-12: “the low performance of the model for extreme summer storm**
206 **events indicated the inadequacy of rainfall measurement”.** Cross validation shows
207 **that storm-runoff parameter (B) which controls the highflow to a high extent varies**
208 **if the calibration period changes (0.2 to 0.8), so you can’t simply attribute the poor**
209 **model performance to the lack of rainfall measurement for the extreme summer**
210 **events!**

211 *Yes, many factors should be responsible for the low performance for the high flow,*
212 *including model input (precipitation is the most important), model parameter and model*
213 *structure. Model structure could be the uncertainty source, which is, however, difficult to*
214 *quantify. Also, as the THREW model has been applied to a dozen of watersheds with varied*
215 *climatic/geographic characteristics (e.g., Tian et al., 2012), we have confidence to say that*
216 *the corresponding model structure reflects the-state-of-the-art modeling approach. Model*
217 *parameter sensitivity results show that the most sensitive parameter to high flow is B and WM*
218 *(see Table 1. In the reply to comments of Prof. Schaefli), and the two parameters are*
219 *calibrated on the high flow separately according to an optimized NSE value. The low*
220 *performance can be contributed to the model input, i.e. insufficient of rainfall measurement.*

221 **16. Some mistakes in writing should be taken care of before publication including but**
222 **not limited to: a. Page 1262, line 12: a similar procedure for temperature: : :!a**
223 **similar procedure as temperature: : : b. Page 1262, line 26: downloaded from the**
224 **website: : : ! downloaded from the NASA website c. Page 1263, line 10: was**
225 **combined ! were combined d. Page 1265, line 8: annual mean ! inter-annual mean e.**
226 **Page 1266, line 12: indexes ! indices f. Page 1271, line 15: years have ! years with g.**
227 **Page 1274, line 9: calibration data ! calibration period**

228 *Thanks, we will correct these and some other mistakes.*

229

230 **Reference**

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243 runoff generation mechanisms in the Blue River basin, Oklahoma. J. Hydrol, 418, 136-149,
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245 Zhang, S., Gao, X., Ye, B., Zhang, X. and Hagemann, S.: A modified monthly degree-day
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248

249