Hydrol. Earth Syst. Sci. Discuss., 8, C3944–C3953, 2011
www.hydrol-earth-syst-sci-discuss.net/8/C3944/2011/

Hydrology and Earth System Sciences Discussions

Interactive comment on "Evaluation of the transferability of hydrological model parameters for simulations under changed climatic conditions" *by* S. Bastola et al.

S. Bastola et al.

satish.bastola@nuim.ie

Received and published: 9 September 2011

Response to interactive comment from G. Heuvelmans on Evaluation of the transferability of hydrological model parameters for simulations under changed climatic condition

Thank you for the comments and suggestions. In the text below we try to answer all the questions formulated. We believe the comments and suggestions from G. Heuvelmans were very helpful in improving the manuscript. If you consider that it is still not enough, please do not hesitate in contacting us. We want to express our apologies if some of

the explanation in some cases is too scant and/or unclear.

Response to General Comments: The idea of using climatic conditions, defined using annual precipitation, is based on some recent studies which show a link between model parameters and climatic conditions (e.g., Merz et al., 2011, Vaze et al., 2011). In this study, the distribution of model parameters of the HYMOD model, for two different sub-periods is shown in Figure 1 and provides empirical support for the argument that model parameters and climate conditions are linked.

Additionally, Fig. 2 shows the percentage change in the median value of parameters of the HYMOD and TOPMODEL models, when moving from dry to wet calibration periods. The HYMOD parameters Cmax (maximum storage capacity), Alpha (parameter that partitions the water in excess of storage capacity between quick and slow reservoir) and Kq (inverse of time constant) increased by nearly 5%. Bexp, which characterises the spatial variability of the catchment, decreased by a similar amount. For TOPMODEL, the parameter Szm (which controls the effective depth of the catchment soil profile) decreased when moving from dry to wet calibration period. However, the parameter T0 (which defines the transmissivity of the catchment soil profile when saturated to the surface) and Td (the time constant for the vertical flux) increased for the wet calibration dataset. This observation is in close agreement with the study of Bastola et al. (2009) which observed low values of Szm on river basins receiving high rainfall or characterized as having a high wetness index, and a high value of Td for basins receiving high rainfall compared to basins receiving lesser rainfall. However, such relationships should be treated with caution due to the uncertainty in model parameters, data and objective criteria.

Furthermore, as rightly pointed out by the reviewer, the criterion for splitting the data in wet, average and dry conditions is the crucial point of the method. These threshold values were used firstly to divide the observation period 1961 to 1990 into three sub-periods of 10 wet (higher than green line in Fig 3), 10 dry (less than red line), and 10 average (years falling between two lines). The values are chosen iteratively such that each sub period contains 10 years of data. The threshold values for the observational period (1971-2000) are shown in Figure 3.

If the splitting criterion is not representative of the expected future climate change then the transfer of parameters between wet and dry sub datasets would say nothing about the transfer of parameters from present to future climatic conditions. Therefore, the threshold valued identified during the calibration period were not used to define the climatic condition for the future. But instead, the threshold values are recalculated for the future period based on 30 years of future data, such that each of the three sub-periods contain 10 years of data. Figure 4 shows the threshold value for the future time period for both the Boyne and Moy river basins. The information will be added to the revised manuscript.

The above figure and discussion will be included in the revised manuscript to improve the clarity in the methodology presented in this study.

Response to minor comments: p. 5893, l 26-28: it is stated that geographical transferability is more problematic than temporal transferability. This is true if the spatial variation of catchment and rainfall properties that are relevant for runoff generation is larger than the temporal variation of these properties. But if you are simulating the impact of future land use or climate change scenarios, then the temporal variation might become larger than spatial variation, so that temporal parameter transfers might become more problematic than spatial transfers. Response: We agree with the reviewer that if the temporal variation of catchment characteristics and rainfall properties is greater than spatial the temporal transferability could be problematic. The statement is suitably modified to improve clarity. - p. 5894 line 10-11: '...only relatively few studies have looked into the temporal transferability of model parameters'. I don't think this is the case: in a 'standard' study, only split-sample tests are performed subdividing a dataset in a calibration period followed by a validation period. This is a kind of temporal transferability. Response: We agree with reviewer that split- sample test are usually performed by subdividing a dataset in a calibration period followed by a validation pe-

riod. The statement has been rewritten in the revised manuscript. - p. 5898 line 5-9: when did you consider a parameter set as behavioural? Which NSE, volume error etc. did you use as threshold value to distinguish between behavioural and non-behavioural sets? Moreover, I do not understand what is meant with 'count efficiency' and with the last criterion. Response: In this study, the threshold value of 0.6 (NSE) was selected as a threshold value to differentiate between behavioural and non behavioural parameter sets. The selection of threshold values were made based on a sensitivity analysis where the width of the prediction interval (ΔQ), count efficiency (CE) and the number of behavioural simulations (NB), were estimated for different threshold values, namely NSE of 0.3, 0.5, and 0.7. For all models the ΔQ, CE and NB increased with a decrease in value of the threshold and vice versa. However, the rate of decrease of ΔQ, CE, and NB are (5%, 15%, 40%, respectively for ΔQ, CE and NB) much smaller when moving the threshold value from 0.3 to 0.5 than when moving it from 0.5 to 0.7 (25%, 37% and 73%, respectively for ΔQ, CE and NB). The criterion to evaluate the performance of each model includes; a) The performance of the median prediction, b) the percentage of observation encapsulated within the prediction interval (CE) and c) the average width of the 90% prediction interval (ΔQ) for each model during the calibration and validation period. The definitions for each criterion are included in the revised manuscript. - p. 5898, line 16-19: here, only 1 criterion is mentioned, whereas on line 5-9, 4 criteria are presented. Why this difference? Response: we express our apology. The text has been modified to improve clarity. - p. 5899, line 7-8: If I get it right, there is not always a loss in NSE; for HYMOD, for example, the calibration for the dry period seems to result in a higher NSE for the wet than for the dry period. . The same applies to the NAM model. Response: the text has been suitably modified in the revised version. - p. 5899, line 16-19: can this difference in model structure explain the observed differences in model performance? Can this be explained in terms of runoff generating mechanisms? Response: Unlike HYMOD and NAM, TANK uses two outlets to simulate surface runoff. This nonlinear structure in the surface reservoir allows TANK to represent diverse hydrograph types. TOPMODEL uses an exponential store where output is exponentially related to storage. The exponential store is generally considered to be a tool for recession and base flow simulation but, as part of a rainfall runoff model, it can also play an important role in the simulation of high flow events. The above discussion is included in the revised manuscript. - p. 5900 (bottom): figure 5 is referred to on line 24, but the lines following this reference seem to refer to figure 4. I can't find any discussion or conclusion about the results presented on figure 5. Response: Fig 5 shows the monthly flow simulated with dry and wet basin simulators for two sub-periods (dry and wet). In terms of seasonal simulations, both simulations are alike. The above discussion for figure 5 is included in the revised manuscript. - p. 5901 line 9-10: It is stated that the predictions are similar with and without parameter updates. From Table 2, it can also be concluded that using different parameter sets for different climatic conditions, does not really improve the model predictions. Sometimes, the performance for the time variant parameters is even worse than the performance obtained with the time invariant parameters. This might mean two things: 1. That parameter updates are not really needed, because the same parameter set delivers predictions with a similar degree of reliability in varying climatic conditions. 2. That the updating scheme is inadequate (for example, because you ignore the impact of extreme events). What is the most probable explanation in this study? Response: It is true that if the splitting criterion is not representative for the expected future climate change, the updating scheme will be inadequate. However, the threshold value, that differentiates different climatic periods, is in fact derived from the future projection (derived from HADCM3 A2 data sets). Therefore, it is more likely that same parameter sets deliver predictions with a similar degree of reliability in varying climatic conditions. This discussion is included in the revised manuscript. Merz, R., J. Parajka, and G. Blöschl (2011), Time stability of catchment model parameters: Implications for climate impact analyses, Water Resour. Res., 47, W02531, doi:10.1029/2010WR009505. Vaze, J., Post, DA., Chiew, FHS., Peraud, JM., Viney, N., Teng, J. (2010), Climate nonstationarity - Validity of calibrated rainfall-runoff models for use in climate change studies, J. Hydrol., 394: 447–457. doi:10.1016/j.jhydrol.2010.09.018. Bastola, S., Ishidaira, H.,

and Takeuchi, K. (2008), Regionalisation of hydrological model parameters under parameter uncertainty: A case study involving TOPMODEL and basins across the globe, J. Hydrol., 357(3–4), 188–206.

List of figures

Figure 1 Histograms of the behavioural sets of model parameters estimated with dry and wet calibration data sets.

Figure 2 Percentage change in model parameter when moving from dry calibration to wet calibration period (a) HYMOD (b) TOPMODEL.

Figure 3 Division of the observation period 1961 to 1990 into three sub-periods of, 10 wet (higher than Green continuous solid line), 10 dry (less than red line), and 10 average (year falling in between two lines) (a) Moy river basin and (b) Boyne river basin

Figure 4 Division of the future projection 2071 to 2100 into three sub-periods of, 10 wet (higher than Green continuous solid line), 10 dry (less than red line), and 10 average (year falling in between two lines) (a) Moy river basin and (b) Boyne river basin

Please also note the supplement to this comment:
http://www.hydrol-earth-syst-sci-discuss.net/8/C3944/2011/hessd-8-C3944-2011-supplement.pdf

Interactive comment on Hydrol. Earth Syst. Sci. Discuss., 8, 5891, 2011.

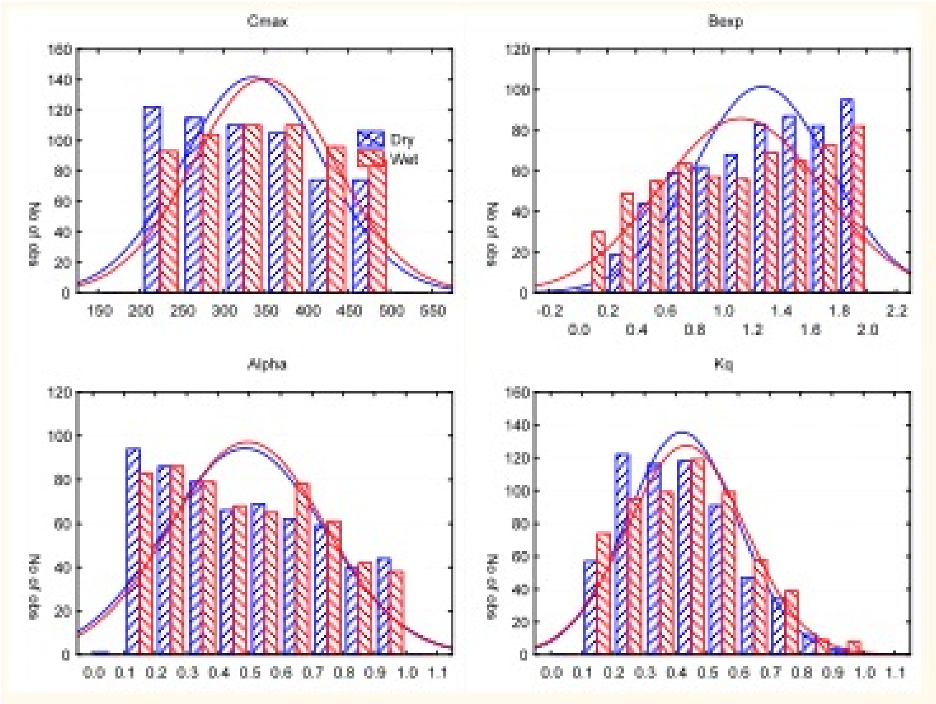

Fig. 1. Figure 1 Histograms of the behavioural sets of model parameters estimated with dry and wet calibration data sets.

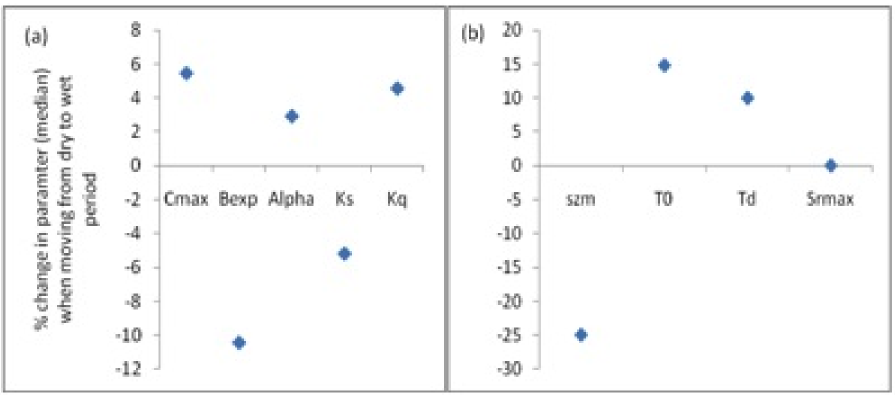

Fig. 2. Figure 2 Percentage change in model parameter when moving from dry calibration to wet calibration period (a) HYMOD (b) TOPMODEL.

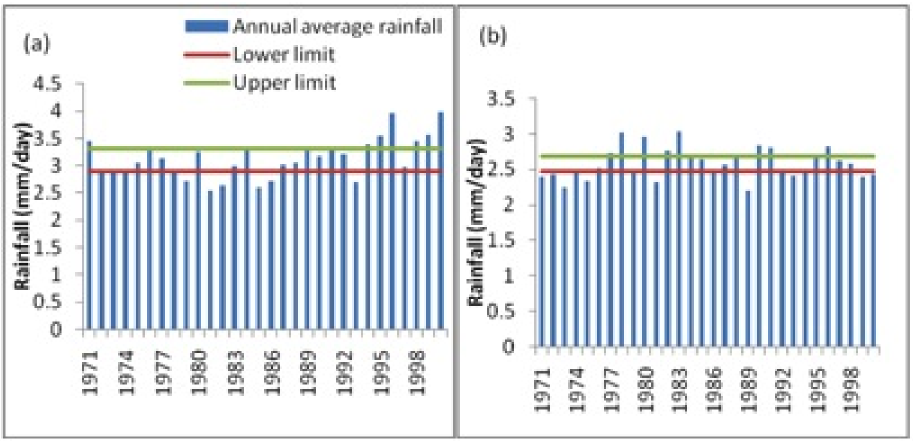

Fig. 3. Figure 3 Division of the observation period 1961 to 1990 into three sub-periods of, 10 wet (higher than Green continuous solid line), 10 dry (less than red line), and 10 average (year falling in betwe

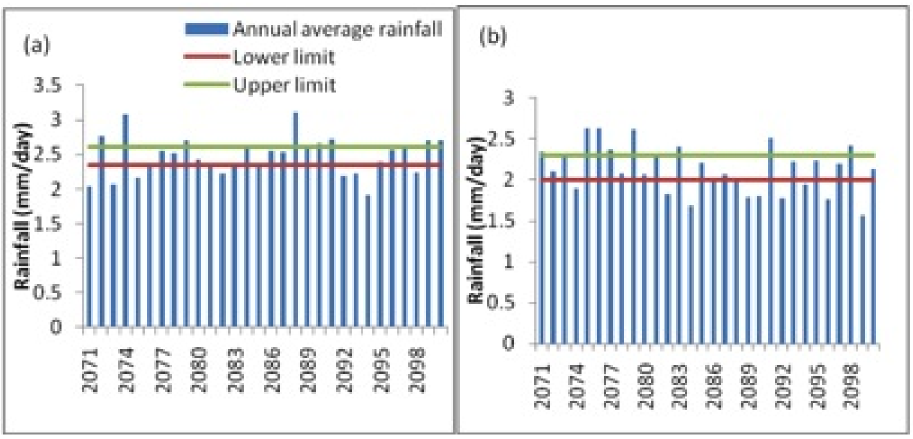

Fig. 4. Figure 4 Division of the future projection 2071 to 2100 into three sub-periods of, 10 wet (higher than Green continuous solid line), 10 dry (less than red line), and 10 average (year falling in betwe