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Predictability of low flow - an assessment with simulation experiments

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Abstract

Since the extreme summer of 2003 the importance of early drought warning has become increasingly recognized even in water-rich countries such as Switzerland. Spring 2011 illustrated drought conditions in Switzerland again, which are expected to become more frequent in the future. Two fundamental questions related to drought early warning are: 1) How long before a hydrological drought occurs can it be predicted? 2) How long are initial conditions important for streamflow simulations? To address these questions, we assessed the relative importance of the current hydrological state and weather during the prediction period. Ensemble streamflow prediction (*ESP*) and reverse *ESP* (*ESP_{rev}*) experiments were performed with the conceptual catchment model, HBV, for 21 Swiss catchments. The relative importance of the initial hydrological state and weather during the prediction period was evaluated by comparing the simulations of both experiments to a common reference simulation. To further distinguish between effects of weather and catchment properties, a catchment relaxation time was calculated using temporally constant average meteorological input. The relative importance of the initial conditions varied with the start of the simulation. The maximum detectable influences of initial conditions ranged from 50 days to at least a year. Drier initial conditions of soil moisture and groundwater as well as more initial snow resulted in longer influences of initial conditions. The catchment relaxation varied seasonally for higher elevation catchments, but remained constant for lower catchments, which indicates the importance of snow for streamflow predictability. Longer persistence seemed to also

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stem from larger groundwater storages in mountainous catchments, which may motivate a reconsideration of the sensitivity of these catchments to low flows in a changing climate.

Keywords: streamflow predictability, low flow, ensemble streamflow prediction, reverse ensemble streamflow prediction

1 Introduction

In many parts of the world people are aware of droughts as natural hazards with significant impacts on many sectors especially when they persist for long periods or occur frequently (e.g. Tallaksen and van Lanen, 2004; Dijk et al., 2013; Viste et al., 2013). However, only recently, scientists and stakeholders in Europe have become concerned not only about floods and their forecasting, but also about droughts. Drivers of this increasing interest include recent droughts such as in summer 2003 (Rebetez et al., 2006) and in spring 2011, which have made water rich countries like Switzerland become more aware of impacts and risks related to droughts. So far, the main concerns in Europe regarding droughts are of economic, environmental, and social importance (e.g. Stahl et al., 2012). During and after droughts, conflicts between different water users can become more frequent and water management has to adapt to meet the different interests as well as possible. For these reasons drought early recognition has become an issue. The basic objective of drought early recognition is to provide timely warning, so that damages can be reduced or even avoided. However, little has been done regarding forecasting and early warning of droughts in Europe. The severity of a drought depends clearly on the climatological deficit of water, but also on the hydrological system that has to cope with this deficit. There were many attempts to quantify droughts by indices based on meteorological variables such as the Palmer drought severity index (Palmer, 1965), deciles (Gibbs and Maher, 1967), the surface water supply index (Shafer and Dezman, 1982), the standardized precipitation index (McKee et al., 1993) or the standardized precipitation and evapotranspiration index (Vicente-Serrano et al., 2010). Each of these indices has its own strengths and weaknesses. Drought indices based on meteorological variables are important, but not sufficient to describe and understand the severity of a hydrological drought. Hence, to recognize locally critical conditions early and provide that information to decision makers, requires both information of the climatological anomalies as

31 well as an understanding of the underlying hydrological systems.
32 The persistence of a system is a measure of how a hydrological condition at a
33 certain point in time can influence the following period and can also be seen
34 as the memory of the system. Catchments with a small storage also usu-
35 ally have a small persistence while catchments with large storages can have
36 longer persistences. The predictability of streamflow and other hydrological
37 variables is highly connected to persistence and there exist various methods
38 to estimate persistences. A classical approach to estimate short term per-
39 sistence is to calculate the autocorrelation of the time series of streamflow
40 observations (e.g. Vogel et al., 1998; Pagano and Garen, 2005). Applying the
41 autocorrelation to highly seasonal data like streamflow data means that they
42 first need to be de-seasonalized before a signal other than seasonality can be
43 found from the autocorrelation can be found. De-seasonalization procedures
44 for hydrological data, however, often require calibration themselves, as the
45 seasonality rarely corresponds to calendar dates (Hipel and McLeod, 1994).
46 Several recent studies try to quantify the impact of initial conditions on
47 the predictability of hydrological conditions. Snow cover (Gobena and Gan,
48 2010; Mahanama et al., 2012), catchment size (Li et al., 2009), North Atlantic
49 Oscillation (NAO), El Niño-Southern Oscillation (ENSO) driven by the Sea
50 Surface Temperature (SST) (e.g. Bierkens and Van Beek, 2009) are generally
51 found to be sources of predictability and they are all highly dependent on the
52 region, system and season. While temperature and precipitation are in part
53 predictable because of the low-frequency variability in global energy stores,
54 particularly in the ocean, (Westra and Sharma, 2010; Feng et al., 2011), on a
55 local scale there are feedbacks because of, for instance, albedo or catchment
56 moisture storages that affect the partitioning between sensible and latent heat
57 fluxes. Predictability in streamflow is controlled by storages, including snow,
58 soil moisture and groundwater, which attenuate the high-frequency rainfall
59 variability to a lower-frequency streamflow response. Singla et al. (2012)
60 assessed the predictive skill of seasonal hydrological forecast in France with
61 two experiments looking at the influence of land surface initial states on the
62 one hand and atmospheric forcing on the other hand. They focused on the
63 spring season as it is critical to the onset of low flows and droughts. One
64 of their important findings was that the predictability of hydrological vari-
65 ables in France mainly depends on temperature and precipitation in lower
66 elevation areas and mainly on snow cover in high mountains. We built on
67 these studies by looking at the predictability of streamflow with focus on low
68 flows in Switzerland using a conceptual hydrological model. These models

69 are important tools in hydrology as they are able to capture dominant catch-
70 ment dynamics while remaining parsimonious and computationally efficient
71 (Kavetski and Kuczera, 2007). Conceptual hydrological models can reach, for
72 specific purposes, considerable performance and, thanks to their computa-
73 tional efficiency, can also be used in ensemble prediction systems (Cloke and
74 Pappenberger, 2009). In flood forecasting systems conceptual models like
75 the NAM model (Van Kalken et al., 2004), the Sacramento model (Grijsen
76 et al., 1993), the PDM model (Moore and Jones, 1997) and the HBV model
77 (Bürgi, 2002) are often applied and use for low flow ensemble forecasting is
78 also emerging (Fundel et al., 2013).
79 In this study we used the HBV model (Bergström, 1992; Lindström et al.,
80 1997) to perform streamflow simulation experiments and to answer the fol-
81 lowing questions: How long is the persistence of the initial hydrological state
82 in model simulations of streamflow and does it vary in space and time? Can
83 the persistence be attributed to catchment storage?

84 **2. Data and Methods**

85 *2.1. Data*

86 The catchments investigated in this study are meso-scale (3 to 350 km²),
87 near natural catchments located in Switzerland (Figure 1). The mean el-
88 evation of the catchments ranges between 480 m a.s.l. and 2400 m a.s.l.
89 (Table 1). Henceforth, specific catchments are referred to by catchment
90 numbers (Table 1). The data used are daily streamflow from the selected
91 Swiss catchments over the period 1970 to 2008 (FOEN, 2011). The meteo-
92 rological forcing variables for the HBV model, precipitation and temperature,
93 stem from interpolated observations from climate stations (MeteoSwiss) in
94 Switzerland. The selection of the meteorological stations as well as inter-
95 polation and aggregation of the variables for each catchment were carried
96 out by the pre-processing tool WINMET (Viviroli et al., 2009). In brief, the
97 spatial and temporal interpolation of observed meteorological variables was
98 based on elevation-dependent regression, inverse distance weighting, Kriging
99 and a simple elevation lapse-rate for temperature data (more details can be
100 found in Viviroli et al. (2009)). A clear seasonal variation of precipitation
101 can be observed for the catchments included here, with winter months re-
102 ceiving about half of the precipitation compared to summer months. The
103 inter-annual variation is similar for all months and about twice as large as
104 the seasonal variation.

105 *2.2. Methods*

106 To quantify the persistence of current hydrological states in streamflow
107 and the influence of weather during prediction we set up three model exper-
108 iments using the hydrological model HBV in the version HBVlight (Seibert
109 and Vis, 2012) (Figure 2).

110 *2.2.1. Model calibration*

111 The HBV model was calibrated for each catchment with the genetic cal-
112 ibration algorithm (GAP), which is included in HBVlight (Seibert and Vis,
113 2012). With GAP, optimized parameter sets are found by an evolution of
114 parameter sets using selection and recombination (Seibert, 2000). An ensem-
115 ble of 100 parameter sets was generated for each catchment, based on 100
116 calibration trials. The mean absolute relative error, F_{MARE} (eq. 1), served
117 as the objective function for the calibration, as the emphasis was on low to
118 medium flows. Its values range between minus infinity and the optimum at
119 one.

$$F_{\text{MARE}} = 1 - \frac{1}{n} \sum_{i=1}^n \frac{|Q_{\text{obs}}(i) - Q_{\text{sim}}(i)|}{Q_{\text{obs}}(i)} \quad (1)$$

120 *2.2.2. Estimation of persistence and catchment relaxation*

121 The model input consists of time series of daily precipitation and tem-
122 perature as well as mean monthly potential evapotranspiration (Penman,
123 1948). The first two experiments a) and b) were set up much like the ex-
124 periments in the study of Shukla and Lettenmaier (2011) and the ensemble
125 streamflow prediction (*ESP*) and the reverse ensemble streamflow prediction
126 (*ESP_{rev}*) approach of Wood and Lettenmaier (2008) (Figure 3). However,
127 in this study 100 parameterizations were used for each ensemble member,
128 which allows more robust interpretation by using the ensemble mean as well
129 as quantification of parameter uncertainty effects. Experiments a) and b)
130 evaluate both the influence of initial conditions and weather during predic-
131 tion on the prediction skill.

132 The simulation experiments differed in the time series that were used as
133 warming up periods to derive initial conditions, and the time series that
134 were used during the prediction period. In experiment a), during the warm-
135 ing up phase the HBV model was forced with different meteorological time
136 series and the forcing during the prediction was the climatology for all simu-
137 lations. The climatology, i.e., the long term mean annual series of precipita-
138 tion and temperature, was computed as 365 arithmetic means of the different

139 years. Experiment b) was the reversed version of experiment a); the time
140 series had identical initial conditions, stemming from the climatology. In
141 the simulations (365 days each), the HBV model was forced with different
142 meteorological time series to derive 'predictions' (Figure 3). For both exper-
143 iments reference runs were performed: in experiment a) the long term mean
144 was used for both warming up and simulation, in experiment b) the same
145 year as in the experimental run was used for the simulation and the previous
146 chronological year was used for the warming up period. By comparison to
147 reference simulations, the two experiments can serve to estimate streamflow
148 persistences that can again be an estimate of the potential streamflow pre-
149 dictability.

150 A third experiment was designed to distinguish further between the influence
151 of the catchments themselves and the meteorological conditions. A relaxation
152 time for the catchments was calculated, defined as the time needed for the
153 system to reach a new equilibrium after being brought off balance (e.g. Graf,
154 1977; Ahnert, 1987; Roering et al., 2001). The warming up in experiment
155 c) was the same as in experiment a). The forcing during the simulation was
156 kept constant and the average annual daily precipitation, mean annual tem-
157 perature and zero evapotranspiration were used. The precipitation was then
158 distributed to correspond to realistic conditions with precipitation on about
159 30% of the days, i.e., three times the average precipitation was used as forc-
160 ing on every third day and zero precipitation otherwise. Before running the
161 simulations the initial snow conditions were all set to zero. This was done to
162 remove the influence the melting of accumulated snow had on the relaxation
163 time estimation, which would obviously have lead to longer relaxation times
164 for catchments with large snow storage. Hence, the catchment relaxation
165 time in this study is the streamflow persistence under constant meteorologi-
166 cal forcing.

167 We defined the persistence [days] in the simulated streamflow as the period
168 from the start of the experiment simulation to the point of convergence (ab-
169 solute average difference equal to 0.002 mm/day) to the respective reference
170 simulation. After convergence there is no impact of the initial conditions
171 visible in the simulations and hence no longer any persistence (see Figure
172 3). For the case with a first convergence that would later spread for some
173 reason (e.g. snow melt), the last convergence of the simulation period after
174 which no spread occurred was used to estimate the persistence (Figure 3,
175 experiment b)). The relaxation time [days] was the start of the simulation
176 from experiment c) to the point of an equal oscillation of all simulations. All

177 experiments a), b) and c) were repeated four times with a shift in the start-
 178 ing date from winter (January 1) to spring (April 1), summer (July 1) and
 179 fall (October 1). The starting date is the time where the initial conditions
 180 are set, i.e., the switch from warming up to prediction mode. All analyses
 181 were performed for each of the 100 parameter sets and for the persistence
 182 estimation as well as the catchment relaxation aggregated to a mean value
 183 in the end.

184 2.2.3. Importance of initial conditions vs. weather during prediction

185 The “prediction skill” of both experiment a) and experiment b) forecasts
 186 were calculated (Shukla and Lettenmaier, 2011). As reference, the reference
 187 simulation from experiment b) was used because it is the chronologically
 188 correct yearly sequence for each forecast/initial condition. Since we were in-
 189 terested in the effects on low flows, we based the measure of prediction skill
 190 of experiment a) (F_{ESP}) and experiment b) (F_{ESPrev}) on the absolute error
 191 as also used in F_{MARE} (eq. 2 and 3).

192

$$F_{ESP} = \frac{1}{n_{ic}} \sum |Q_{ref,b}(t, i) - Q_{sim,a}(t, i)| \quad (2)$$

193 where n_{ic} is the number of initial conditions (26 different years), $Q_{ref,b}(t, i)$ is
 194 the reference of the forecast i at day t and $Q_{sim,a}(t, i)$ is the ensemble member
 195 using the initial condition i at day t .

$$F_{ESPrev} = \frac{1}{n_{fc}} \sum |Q_{ref,b}(t, i) - Q_{sim,b}(t, i)| \quad (3)$$

196 where n_{fc} is the number of forcing ensemble members (26 different years)
 197 and $Q_{sim,b}(t, i)$ is the ensemble member at this day and forecast. The time
 198 dependent ratio F_{ratio} of F_{ESP} and F_{ESPrev} of each experiment was then cal-
 199 culated using Equation 4.

200

$$F_{ratio}(t) = \frac{F_{ESP}}{F_{ESPrev}} \quad (4)$$

201 Values of F_{ratio} larger than one indicate a relatively higher forecast error
 202 due to uncertainties in the weather during prediction compared to the un-
 203 certainties in the initial conditions. This suggests a high contribution of
 204 the weather to the prediction skill (Shukla and Lettenmaier, 2011). Values
 205 of F_{ratio} smaller than one indicate relatively larger uncertainties due to the

206 initial conditions compared to the uncertainties in the weather during pre-
207 dictions, which suggests a high contribution of the initial conditions to the
208 prediction skill. The F_{ratio} of all simulations was calculated for lead times of
209 1, 2, 3, ..., 52 weeks. The values for F_{ratio} were computed for each of the 100
210 calibrated parameter sets and then aggregated as the mean.

211 *2.2.4. Connection of persistence to conceptual storages*

212 The HBV model consists of a number of conceptual storages: snow storage
213 (*Snow*), soil moisture (*SM*), upper groundwater (*SUZ*), and lower ground-
214 water storage (*SLZ*) (Figure 2). The initial storages at the start of each
215 simulation were compared to the estimated persistences from experiment a).
216 The actual initial hydrological state at the start of each simulation was trans-
217 formed to a relative initial hydrological state by using the long term average
218 conditions of the respective month in which the simulation start was set.
219 For instance in winter the relative initial state is the ratio of the state on
220 January 1 in a particular simulation and the average January state condition
221 from the entire 26-year-period. The relation of initial conditions of each stor-
222 age (*Snow*, *SM*, *SUZ*, and *SLZ*) from the 21 years of each catchment to
223 the respective persistences were then analyzed by calculating the Spearman
224 rank correlation between initial state and persistence for each catchment.
225 Correlations with a p value smaller than 0.05 were considered statistically
226 significant.

227 **3. Results**

228 *3.1. General model performance*

229 The model performance (F_{MARE} , eq. 1) of the best parameter sets varied
230 between 0.64 and 0.84 for the 21 catchments with a median of 0.77. Good
231 model performance could be achieved with varying individual parameter val-
232 ues and on average the best parameter values for a single catchment varied
233 over 10 to 66 % of the tested parameter ranges.

234 *3.2. Persistence in streamflow simulations*

235 Experiment a) and b) resulted in similar estimates for persistence in
236 streamflow for all catchments ranging between 50 days of persistence to more
237 than a year (Figure 4). There was a tendency of higher elevation catchments
238 to have longer persistences. We found strong correlations between the mean

239 of the persistence estimates and the mean catchment elevations for all sea-
240 sons (Table 2). The difference in estimates for the different starting dates
241 was small. For spring and summer catchments 9 to 18 have higher persis-
242 tence estimates for experiment a) than for experiment b). This difference is
243 still visible for the values based on fall simulations, but is not apparent for
244 the winter simulation. The variability of the persistence estimates caused
245 by parameter uncertainty (i.e., the spread among the simulations of the 100
246 parameter sets) was higher than that caused by the inter-annual variabil-
247 ity (i.e., the spread among the simulations for the different years) (Figure
248 5). Especially simulations starting in summer and fall showed an increased
249 variability from parameter uncertainty for many catchments.

250 3.3. Catchment relaxation

251 The catchment relaxations varied between about three months to a year.
252 For the low elevation catchments the catchment relaxation remained the
253 same for all seasons, while the higher elevation catchments showed differences
254 when starting the simulations at different dates. In Figure 6 the estimated
255 mean persistences and the catchment relaxation times are compared. All
256 catchments but catchment 18 have longer persistences than catchment relax-
257 ations. The difference between catchment relaxation and mean streamflow
258 persistence was smallest in spring and became larger in summer, fall and
259 winter. The largest difference between relaxation and persistence was seen
260 in fall.

261 3.4. Importance of initial states vs. weather during prediction

262 F_{ratio} was found to vary with the season of the start of the simulation
263 for the different catchments (Figure 7). For clarity, it should be mentioned
264 again that the F_{ratio} indicates the relative influence of the initial conditions
265 in comparison to the weather, while the persistence indicates the influence of
266 the initial conditions on the predictions regardless of the weather. In spring,
267 the F_{ratio} with values smaller than one had the longest lead times in most low
268 elevation catchments and the highest elevation catchments with lead times
269 ranging from 8 to 11 weeks. Middle and high elevation catchments have only
270 very short lead times of about a week, during which the initial conditions
271 have greater uncertainties than the weather during prediction. In summer,
272 the length of the lead times with an F_{ratio} smaller than one varied for the
273 catchments, but the pattern could not be clearly related to catchment char-
274 acteristics. However, many low elevation catchments have an F_{ratio} smaller

275 than one for lead times from 9 to 10 weeks. The shortest lead time with
276 an F_{ratio} smaller than one when starting in summer was one week and the
277 longest lead times with an F_{ratio} smaller than one 12 weeks. In fall, there is
278 a clear tendency of greater uncertainties of the initial conditions for a longer
279 period than those for weather for higher elevations. The shortest lead time
280 with an F_{ratio} smaller than one when starting in fall was five weeks, and the
281 longest lead time 18 weeks. In winter for all but the high elevation catch-
282 ments the uncertainties of the initial conditions relative to the uncertainties
283 of the weather decreased quickly and for most catchments with an F_{ratio}
284 smaller than one, lead times were at the maximum one to three weeks. For
285 the high elevation catchments the lead times with an F_{ratio} smaller than one
286 ranged from 5 to 19 weeks, and for the three highest elevation catchments
287 with an F_{ratio} smaller than one, the range was from 14 to 19 weeks.

288 *3.5. Hydrological states and streamflow persistence*

289 The main snow accumulation happens in early spring and winter. For
290 most catchments, more snow during the initial conditions in winter were re-
291 lated to longer persistences (Figure 8). The Spearman correlation coefficients
292 ranged between 0.46 and 0.66 for the statistically significant positive correla-
293 tions in winter (Figure 10). In spring this relationship could only be found for
294 a few catchments. Neither in spring nor in winter, could the catchments with
295 significant correlations be attributed to the catchment properties. In summer
296 only the highest elevation catchments would show snow effects, while in fall
297 there might be single days of single years where snow starts to accumulate.
298 For this reason we looked only at the relation between persistence and snow
299 storage in winter and spring.

300 Drier initial soil moisture conditions in winter and spring for most catch-
301 ments were related to longer persistences (Figure 9). The initial conditions
302 of the other seasons showed both positive and negative correlations for differ-
303 ent catchments (Figure 10). The negative correlations in spring and winter
304 were found for low and middle elevation catchments. In summer the correla-
305 tions could not be attributed to catchment properties. However, the positive
306 correlations in fall were mainly found for low elevation catchments, while the
307 negative correlations were rather found for middle and high elevation catch-
308 ments.

309 The initial conditions of the upper groundwater storage (SUZ) showed a
310 clear tendency related to the persistence only in spring. Here, drier initial
311 SUZ led to longer persistences for most catchments. There were significant

312 correlations for the low and high elevation catchments, but not for the middle
313 elevation catchments (Figure 10). The initial conditions in the other seasons
314 were both positively and negatively correlated to the persistence. For win-
315 ter only very few catchments showed significant correlations between initial
316 conditions and persistence.

317 The lower groundwater storage (*SLZ*) with a simulation start in spring
318 showed both significant positive and negative correlations to the persistence
319 (Figure 10). In spring negative correlations were found for low elevation
320 catchments, while the positive correlations did not match patterns of catch-
321 ment elevation or size. In fall the positive correlations were found for the
322 low elevation catchments, however, the negative correlations did not show
323 any common pattern with catchment properties. In summer and winter, the
324 correlations did not clearly match any catchment property pattern.

325 4. Discussion

326 4.1. Hydrological model

327 The results regarding persistence and relaxation times are to some de-
328 gree model dependent. However, if a model has been successfully calibrated,
329 differences are probably relatively small. It can be assumed that the impor-
330 tant storages as well as their variability relative to each other are reasonably
331 well represented. The model we used here was somewhat less complex than
332 the VIC model (Liang et al., 1994), which has been used in several of the
333 previous studies on persistence (Wood and Lettenmaier, 2008; Shukla and
334 Lettenmaier, 2011). However, the groundwater routines of HBV and VIC are
335 relatively similar. Using a less complex model allowed us to derive several
336 behaviorable parameter sets and in this way to address parameter uncer-
337 tainty, something that has not been done in the previous studies. From our
338 results the use of an ensemble mean can be recommended, as the variability
339 of the results due to parameter uncertainty was considerable for most of the
340 catchments. The large variability among the simulations that were started
341 in summer and fall when including parameter uncertainty indicates a high
342 uncertainty connected to parameters of the soil routine which control evapo-
343 ration. Seibert and McDonnell (2010) also concluded that it is important to
344 consider parameter uncertainty to obtain reliable results. A high variability
345 due to parameter uncertainty increases the risk for variable and partly ran-
346 dom results if only a single parameter set is used. The ensemble approach
347 used here is a suitable way to ensure robust results.

348 The simulated snow cover was derived from a degree day method, which
349 could be argued to be less accurate than a snow cover simulated with energy
350 balance methods. However, for the spatial and temporal scales looked at
351 here, several studies have shown that the degree day method is an appro-
352 priate approximation (e.g., Rango and Martinec, 1995; Seibert, 1999; Hock,
353 2003; Merz and Blöschl, 2004)

354 The formulation of the potential evaporation can yield large differences in
355 evaporative demand which can affect the calibrated model parameters and
356 thus how the moisture is stored (McMahon et al., 2012). However, any errors
357 in the estimation of the potential evaporation is implicitly considered in the
358 calibration, i.e., parameter values might be influenced, but the catchment
359 behavior in terms of responses and persistences should be influenced less.
360 All these issues related to the model choice have to be considered, also when
361 evaluating the results. However, the main outcomes concerning the influence
362 of initial conditions related to storages within the catchment are represented
363 and that the use of various parameter sets allowed for the estimation of un-
364 certainty derived from the model.

365 Arithmetically averaged precipitation values were used in the climatology
366 time series. While this approach ensures a representative mean precipitation
367 amount, the temporal pattern of precipitation might be changed resulting
368 in more days with some precipitation. During winter this has no effect on
369 the simulated streamflow, but the mean simulated summer streamflow might
370 decrease as more precipitation can be temporarily stored and then be evap-
371 orated. However, in the humid catchments used in this study, the effect on
372 the total streamflow volume is limited. While it is important to be aware of
373 this unrealistic temporal pattern in the precipitation climatology time series,
374 its influence on the results of persistence and relaxation times in this study
375 will not be substantial.

376 *4.2. Prediction skill*

377 Mahanama et al. (2012) started their simulations, as we did, in different
378 seasons and looked at the ratios of the prediction skills (F_{ratio}) for several lead
379 times up to six months. They found that depending on when the simulations
380 were started and the lead time applied, the dominance of initial conditions
381 or weather during prediction changed from more dominant initial conditions
382 for short lead times (mostly 1 month) to more dominant weather during
383 prediction for longer lead times. Mahanama et al. (2012) found that during
384 spring and summer months initial conditions dominated the prediction skill in

385 the U.S. beyond short lead times. We looked at the dominant effect at lead
386 times up to one year and found at the shorter lead times relatively larger
387 uncertainties stemming from the initial conditions and more uncertainties
388 from the weather overall as compared to the initial conditions for all starting
389 dates, which is similar to the findings of Mahanama et al. (2012) and the
390 observations by Wood and Lettenmaier (2008) for the North Western US.
391 However, the distribution of the F_{ratio} changed for different starting dates
392 and for some catchments even more strongly. Shukla and Lettenmaier (2011)
393 noted differences in the ratio of their objective functions for varying dry or
394 wet initial conditions. We observed this as well, as the rather wet initial
395 conditions in spring showed a dominant contribution of the weather during
396 the prediction on the skill for the lower and highest elevation catchments.
397 This changed for the drier initial conditions found in summer, where the
398 uncertainties of the initial conditions are larger for longer compared to the
399 uncertainties of the weather than in spring.

400 *4.3. Variability of the persistence estimation*

401 From the two experiments, the different model parameter sets for the sim-
402 ulations and the different seasonal forecasts as well as initial conditions, we
403 found a distribution of persistence estimates for each catchment. The persis-
404 tence estimates from experiment a) and experiment b) overlapped for most
405 catchments. The persistence estimations from experiment b) were systemat-
406 ically longer in spring and summer for all catchments than the persistences
407 from experiment a). In experiment a), the experiment run as such is a rep-
408 resentation of what we face in reality, an attempt to forecast using a known
409 initial condition and several scenarios of how the weather might be. By using
410 reference simulations based on the true weather, this gave us the opportunity
411 to see how long a present/initial state mattered in deriving the most realistic
412 simulation rather than simply initializing the model with the climatology.
413 Instead, in the reference of experiment a) both warming up and forcing was
414 with the climatology. So, the persistences in experiment a) were computa-
415 tionally much faster to estimate than in experiment b) but the climatology
416 plays a greater role in the definition of the persistence estimation. The role
417 of climatology could be the reason for the observed offset in the persistence
418 estimates for the middle elevation catchments: If the initial conditions were
419 wetter and/or more snow accumulation took place during the models warm-
420 ing up phase, it would take longer to reach the reference simulation that was
421 based on a drier climatology than it would take to reach a reference simu-

422 lation that was based on a realistic seasonal warm up (as in the reference
423 runs from experiment b)). For fall and winter simulations the climatology
424 was likely closer to a realistic seasonal warm up, since we could not observe
425 this offset for those seasons.

426 *4.4. Streamflow persistence vs. catchment relaxation*

427 The estimated streamflow persistences are a combination of both weather
428 and catchment properties. Catchment relaxation times should instead mainly
429 represent the catchment storage properties. The relaxation times in different
430 seasons however can vary slightly as the simulations started with different
431 initial conditions each season and then reached a new balance of the sys-
432 tem. The catchment relaxation time for catchments with a snow dominated
433 streamflow regime were longer in spring compared to the other seasons, which
434 could be explained by filled soil and groundwater storages from the preced-
435 ing winter and fall. Since the lower elevation catchments did not show this
436 seasonal difference we suspect the higher catchments to have larger storages.

437 *4.5. Initial conditions and catchment properties*

438 We found that the persistence estimates were strongly correlated to catch-
439 ment mean elevation. This could partly be explained by an increasing snow
440 influence with elevation, but could also be due to larger aquifers. In the
441 synthetic experiments of Van Loon et al. (2014), who compared warmer and
442 colder climates as well as the effect of varying geology, both increased snow
443 influence and slower aquifer response were found to cause longer drought
444 persistences. In our study, we also found that initial storages of snow and
445 soil moisture were related to the persistence estimates, which corresponds to
446 the conclusion of Van Loon et al. (2014) that seasonality effects cannot be
447 explained by meteorological processes alone. The relation between storage
448 of snow/soil moisture and persistence was also found by Singla et al. (2012)
449 for France and by Mahanama et al. (2012) for the U.S.. While Singla et al.
450 (2012) could distinguish between the importance of snow and soil moisture
451 for elevation classes, we did not find such a clear signal. Instead we saw that
452 the importance of snow, soil moisture and groundwater storage, depended on
453 the starting date of the simulations. When the simulations were started in
454 winter or spring the initial conditions of snow were related to the persistence
455 estimates for many catchments and in summer to the highest with more ini-
456 tial snow leading to longer persistences. Drier initial soil moisture could be

457 connected to longer persistences for lower elevation catchments with simu-
458 lation starts in all seasons but winter. Longer predictabilities connected to
459 drier initial conditions were also found by Fundel et al. (2013). For higher el-
460 evation catchments and winter simulation start wetter initial conditions lead
461 to longer persistences. This can be explained by the absolute size of the soil
462 moisture storage of lower elevation catchments compared to higher elevation
463 catchments. The persistences and initial groundwater storage conditions did
464 not show a general pattern.

465 4.6. *The role of snow*

466 Accumulating and melting snow is an important storage and storage out-
467 flow. Moreover, snow melt fills other storages in the catchment. Hence, when
468 trying to distinguish between meteorological influence and initial conditions
469 with the ESP/ESP_{rev} analysis this double role of snow has to be taken into
470 account. Snow melt that contributed to the initial conditions is attributable
471 to the initial conditions, but snow fall, accumulation and melt during the
472 simulation period will directly influence the meteorological forcing. The high
473 elevation catchments where snow fall could also occur in seasons other than
474 winter showed a different effect than the catchments at middle elevations,
475 where the initial conditions were still more dominant than the meteorological
476 forcing. This could result from the time shift of when the snow accumulation
477 and melt happened.

478 For the persistence estimation, snow storage is directly taken into account,
479 which was visible in both the correlation to the mean catchment elevation
480 and the relation between snow storage and persistence. For the catchment
481 relaxation, the direct snow accumulation and melt was explicitly excluded,
482 even though the snow melt that occurred during the warm-up was included.
483 This remaining snow influence seems critical as we found seasonal differences
484 in the relaxation times of the middle and higher elevation catchments, but
485 not in the lower elevation catchments.

486 Another indication for the role of snow can be seen from the already dis-
487 cussed offset between the results from experiment a) and b), namely that the
488 climatology in the warming up of the reference runs in experiment a) were
489 not as realistic as the warm up of experiment b), which caused greater offsets
490 in the seasons with snow involved.

491 *4.7. Catchment elevation and storage*

492 At high elevations we usually find thinner soils, however, our results chal-
493 lenge the common assumption of less storage in higher elevation catchments
494 and indicate that there might be a larger groundwater storage. This can
495 be explained by large storage features that can be found in mountain catch-
496 ments like talus slopes with high storage capacities. The total storage ca-
497 pacity might also increase with elevation because of a storage volume above
498 drainage level that is higher in mountainous catchments than in rather flat
499 low elevation catchments. We know for example that the highest catchment
500 (catchment 21) from our selection shows extraordinarily high storage capac-
501 ities as water can be stored in deep moraines that make up one third of the
502 entire area and in an additional alluvial storage on the valley floor (FOEN ,
503 2011).

504 *4.8. Predictability of droughts*

505 In this study, the analyses were performed from a low flow perspective, as
506 the objective function during both the calibration and the analysis empha-
507 sized low flow. The persistence estimations showed that for different catch-
508 ments the maximum predictability for streamflow varied from 50 days to more
509 than a year with the tendency to show higher elevation catchments related
510 to longer predictabilities. The persistence estimates did not vary greatly
511 with a change of the starting date of the simulations to another season. The
512 relative influence from weather with respect to initial conditions, however,
513 varied with a change of the starting date of the simulations. In spring the
514 highest elevation catchments had longer lead times with small uncertainties
515 of the initial conditions presumably due to large snow accumulations at the
516 start of the simulations for all years of the ensemble. The lower elevation
517 catchments, however, have, at the time of the start of the simulation, barely
518 accumulated snow, while the snow storage at middle elevation catchments
519 might vary strongly from year to year. This can explain the longer relative
520 influence of the initial conditions on the predictability found for the low eleva-
521 tion catchments, but not in the middle elevation catchments, as the snow can
522 accumulate before or after the starting date of the simulation (April 1). In
523 fall and winter higher elevation catchments tended to have longer lead times
524 of high relative importance of the initial conditions compared to the weather
525 during prediction. This points to a larger influence of the initial conditions in
526 higher elevations which could be due to snow storage as well as other storages.
527 With the tendentially drier conditions in summer there was more variation

528 and the simulations of catchments, no matter at which elevation, had longer
529 or shorter small uncertainty contributions from the initial conditions. The
530 summer F_{ratio} point on the one hand to storage differences, but also to vary-
531 ing summer meteorology for the different catchments. With this study, the
532 question of how long before a drought occurs can it be predicted, cannot
533 readily be answered. However, for the catchments in this study we found
534 ranges of maximum detectable influence of initial conditions from 50 days to
535 more than a year. Further, we found that the catchment elevation matters
536 more than the starting date of the simulation for a maximum predictability
537 of streamflow and that the relative importance of initial conditions compared
538 to the relative influence of the weather during the predictions changes with
539 the season in which the simulation start is set.

540 5. Conclusions

541 We estimated persistences for 21 different Swiss catchments using model
542 simulation experiments performed with the HBV model. The range of the
543 persistence estimates differed between the catchments and showed a strong
544 correlation with mean catchment elevation. Together with the relative influ-
545 ence of weather with respect to initial conditions, the predictabilities ranged
546 from 50 days to more than a year with a decreasing influence of the initial
547 conditions over time. The degree of the decrease was found to be dependent
548 on the start of the simulation. In fall and winter, a longer influence of the
549 initial conditions during prediction was found for higher elevation catchments
550 as compared to the weather. In spring, the initial conditions were relatively
551 more important for the prediction than weather for the highest and lower ele-
552 vation catchments compared to the middle elevation catchments. This might
553 be due mainly to annual snow melt and accumulation variations around the
554 starting date of the spring simulations in the middle elevation catchments.
555 In summer, the initial conditions had differing influence on the predictions
556 and were not related to a specific elevation range.

557 The interpretation of the correlation between higher elevation and longer per-
558 sistences might not be easy without additional information about catchment
559 properties like type and size of aquifers. Compared to the persistence the re-
560 laxation time was lower and the catchment relaxation time varied seasonally
561 for higher elevation catchments but was constant for lower elevation catch-
562 ments, which indicates the important role of snow in persistence estimation.
563 We found that snow and soil moisture as well as groundwater initial condi-

564 tions derived from the model states were related to the persistence estimates.
565 Drier initial states of soil moisture and groundwater and more snow accumu-
566 lation at the start of the simulation led to longer persistence estimates.
567 In opposition to an intuitive expectation from shallow soils in higher ele-
568 vations, we found an indication for larger groundwater storages in higher
569 elevation catchments. This may motivate a reconsideration of the sensitivity
570 of mountainous catchments to low flows in a changing climate.

571

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Table 1: Catchment properties (FOEN , 2011).

Number	Catchment	Area [km^2]	Mean elevation [$ma.s.l.$]	Regime type	Pores [%]	Fissures [%]	Karst [%]
1	Aach	48.5	480	pluvial	14.9	85.1	0.0
2	Ergolz	261	590	pluvial	10.0	0.0	90.0
3	Murg	78.9	650	pluvial	35.0	65.0	0.0
4	Mentue	105	679	pluvial	77.6	22.4	0.0
5	Broye	392	710	pluvial	65.0	35.0	0.0
6	Langeten	59.9	766	nivo-pluvial	18.3	81.7	0.0
7	Rietholz	3.3	795	nivo-pluvial	0.0	100	0.0
8	Goldach	49.8	833	nival	24.3	75.7	0.0
9	Cassarate	73.9	990	pluvial	0.0	100.0	0.0
10	Sitter	261	1040	pluvial	27.7	39.0	33.3
11	Guerbe	117	1044	nivo-pluvial	77.0	17.7	5.3
12	Kleine Emme	477	1050	nivo-pluvial	50.0	35.0	15.0
13	Sense	352	1068	pluvio-nival	36.7	56.8	6.5
14	Emme	124	1189	nival	12.5	86.5	1.0
15	Grande Eau	132	1560	nival	0.0	60.0	40.0
16	Simme	344	1640	glacio-nival	0.0	75.0	25.0
17	Allenbach	28.8	1856	nivo-glaciaire	48.0	44.5	7.5
18	Riale di Calneggia	24	1996	nivo-pluvial	18.6	81.4	0.0
19	Ova dal Fuorn	55.3	2331	glacio-nival	6.3	14.7	74.0
20	Ova da Cluozza	26.9	2368	glacio-nival	21.3	1.0	77.7
21	Dischma	43.3	2372	glacio-nival	31.2	68.8	0.0

Table 2: Spearman rank correlation between mean catchment elevation and mean of the persistence estimates from experiment a) and b).

Start of simulation	Spearman rank correlation	
	Experiment a	Experiment b
Spring	0.59**	0.90***
Summer	0.52*	0.90***
Fall	0.85***	0.89***
Winter	0.81***	0.60**

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

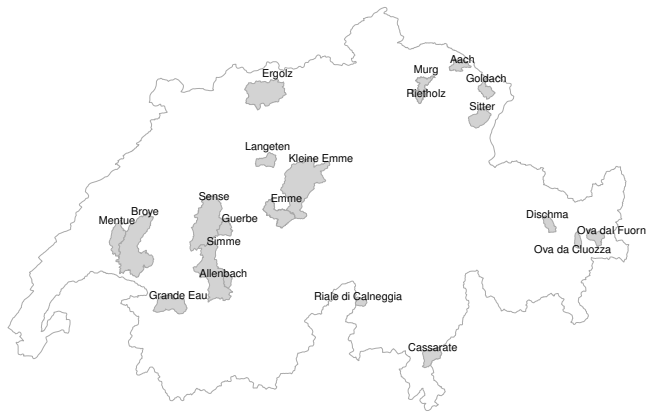


Figure 1: Location of the selected Swiss catchments.

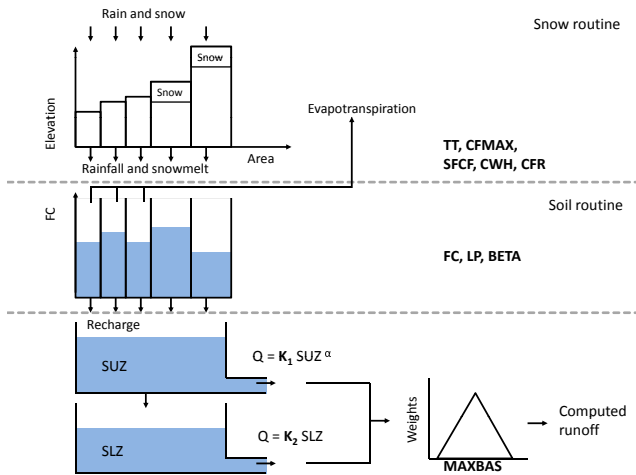


Figure 2: Conceptualization of the HBV model (modified after Uhlenbrook et al. (1999)).

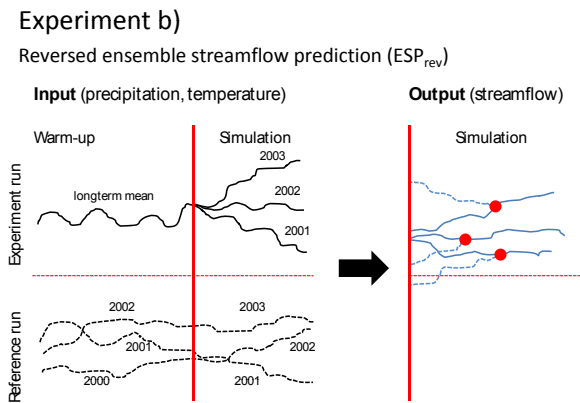
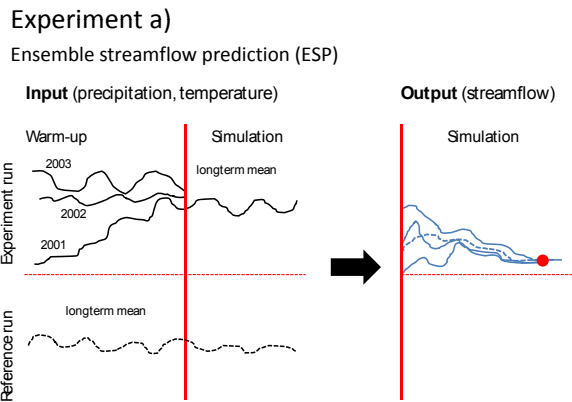


Figure 3: Set up of model experiment a) (ensemble streamflow prediction, ESP) and b) (reverse ensemble streamflow prediction, ESP_{rev}). Dashed lines indicate the reference runs and the red points indicate the persistence.

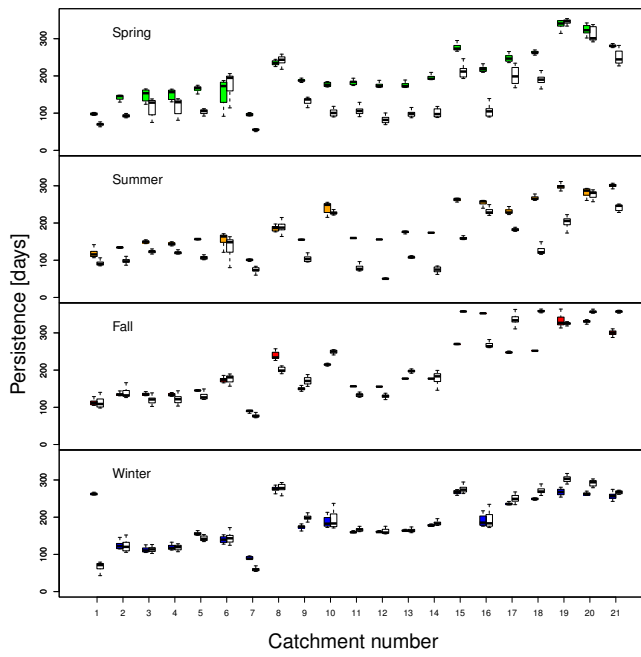


Figure 4: Distributions of the estimations of the persistences from experiment a) and experiment b) for the four starting dates for all catchments. For each catchment two distributions are displayed; the left colored box is the distribution from experiment a) and the right, empty box from experiment b). The catchment mean elevation increases from left to right.

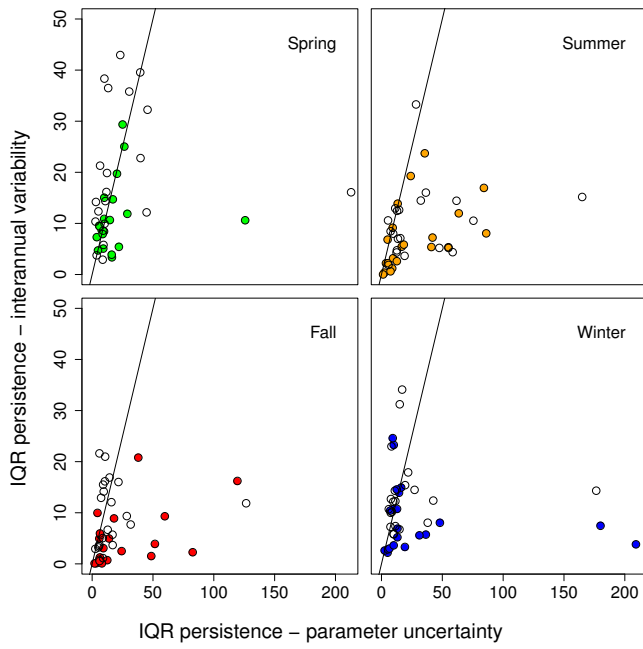


Figure 5: Comparison of the importance of variability of the estimated persistence values due to inter-annual variation and parameter uncertainty. The variability is quantified by the interquartile range, IQR, in the first case computed among the mean values from all 100 parameter sets and in the second case computed from the means of all 26 years. Colored symbols indicate the IQR resulting from experiment a), empty symbols from experiment b).

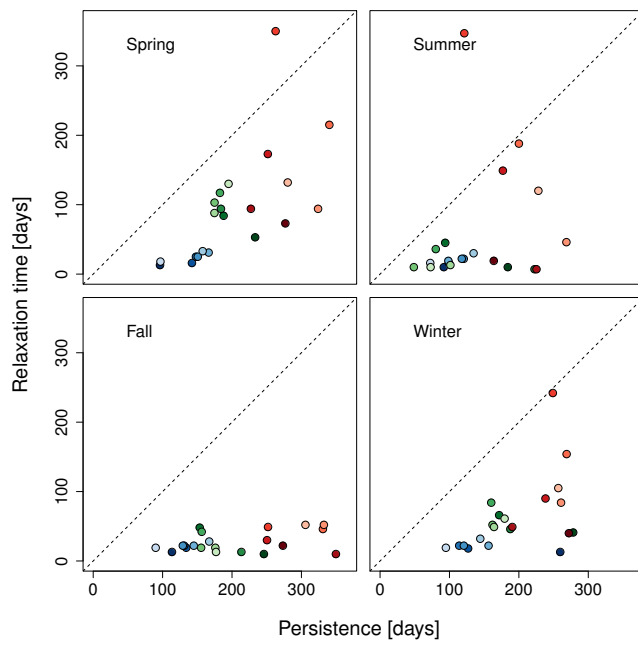


Figure 6: Catchment relaxation times compared to the mean persistence estimates (experiment a)). The colors range from blue for low elevation catchments to red for high elevation catchments.

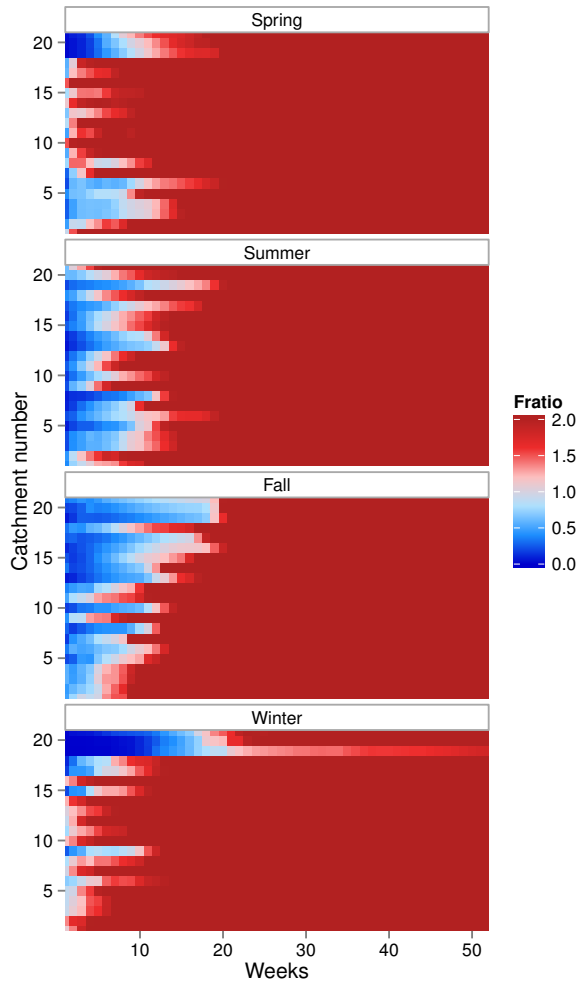


Figure 7: Median of F_{ratio} of the different simulations with lead times starting from one week up to one year in weekly time steps for all catchments and seasons. F_{ratio} values smaller than one, blue colors, indicate a larger uncertainty from the initial condition compared to the weather during the predictions; F_{ratio} values larger than one, red colors indicate a larger uncertainty stemming from the weather during the prediction.

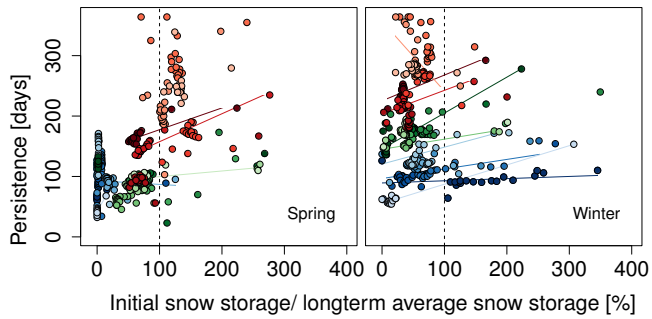


Figure 8: Relation of the initial snow accumulation relative to the snow accumulation during the simulation of the following year and the estimated persistence (experiment a)) for all catchments. Values below 100 indicate that the initial conditions were drier than the average snow accumulation during the simulation. Each color indicates a single catchment and each point a single year. The colors range from blue for low elevation catchments to red for high elevation catchments. For significant rank correlations linear regression lines are drawn.

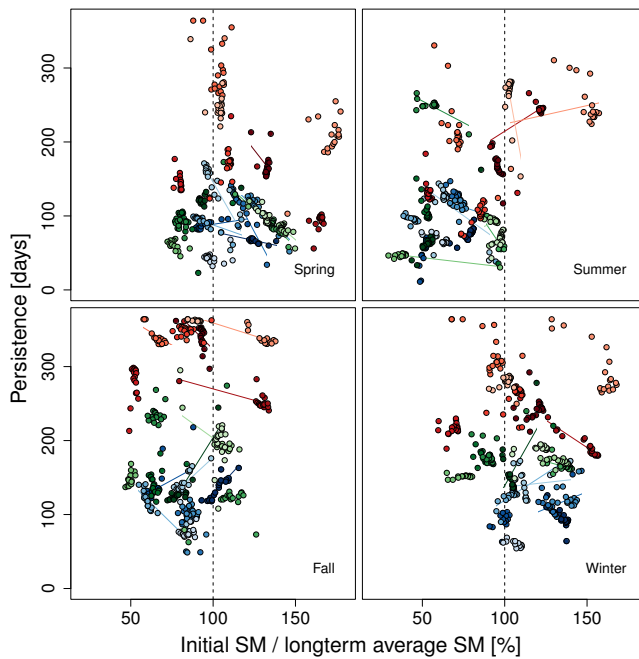


Figure 9: Relation of the initial soil moisture storage relative to the soil moisture storage during the simulation of the following year and the estimated persistence (experiment a)) for all catchments. Values below 100 indicate that the initial conditions were drier than the average soil moisture storage during the simulation. Each color indicates a single catchment and each point a single year. The colors range from blue for low elevation catchments to red for high elevation catchments. For significant rank correlations linear regression lines are drawn.

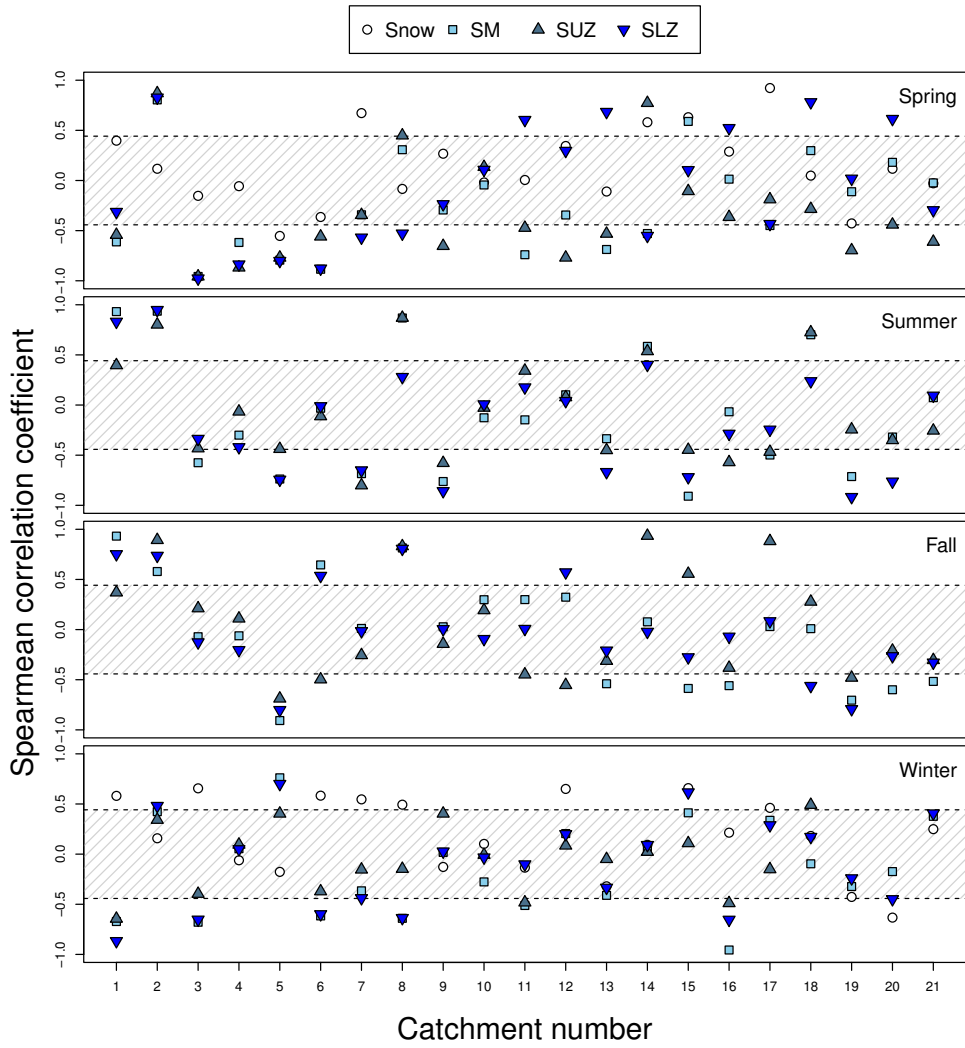


Figure 10: Spearman rank correlation coefficients for the relation between initial conditions of the storages (snow (*Snow*), soil moisture (*SM*), upper groundwater storage (*SUZ*) and lower groundwater storage (*SLZ*)) and persistences (experiment a)). Correlations that are not significant are plotted in the hatched area (p value >0.05).