Using dry and wet year hydroclimatic extremes to guide future hydrologic projections

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Abstract

There are growing numbers of studies on climate change impacts on forest hydrology but limited attempts have been made to use current hydroclimatic variabilities to constrain projections of future climatic conditions. Here we used historical wet and dry years as a proxy for expected future extreme conditions in a boreal catchment. We showed that runoff could be underestimated by at least 35% when dry year parameterizations were used for wet year conditions. Uncertainty analysis showed that behavioural parameter sets from wet and dry years separated mainly on precipitation related parameters and to a lesser extent on parameters related to landscape processes. While inherent uncertainty in climate models still drives the overall uncertainty in runoff projections, hydrologic model calibration for climate impact studies should be based on years that best approximate expected future conditions.

Keyword: Boreal forest, boreal hydrology, climate change, uncertainty assessment, hydroclimatic extremes

1 Introduction

There are growing numbers of studies on climate change impacts on watershed hydrology but these are usually based on long-time series that depict average system behaviour (Bonan, 2008; Lindner et al., 2010: Tetzlaff et al., 2013). As a result, limited attempts have been made to use extreme dry and wet conditions to assess plausible future conditions. Increasing numbers of studies are showing the importance of ensemble projections to create a matrix of possible futures, where the mean provides a statistically more reliable estimate than can be obtained from a single realization of possible future conditions (Bosshard et al., 2013; Dosio and Paruolo, 2011; Oni et al., 2014a; Raty et al., 2014). However, the predictive uncertainty of precipitation projections is still larger than that for temperature (Teutschbein and Siebert, 2012). This inherent uncertainty might further increase in the warmer future as precipitation dynamics become less consistent due to a shift in winter precipitation patterns toward rainfall dominance (Berghuijs et al., 2014; Dore, 2005).

It is unequivocally believed that climate is a first order control on watershed hydrology (Oni et al., 2015a, b; Vörösmarty et al., 2000). Although climate change is a global phenomenon (IPCC, 2007), it will likely also alter local catchment water balances (Oni et al., 2014b; Porporato et al., 2004). Prolongation of drought regimes or increasing frequency of storm events observed in different parts of the world (Dai, 2011; Trenberth, 2012) calls for greater attention on how to constrain uncertainty in predicting extreme dry and wet conditions. While the frequency of hydroclimatic extremes might be low under present day conditions (Wellen et al., 2014), there could be intensification of precipitation events globally as climate changes (Chou et al., 2013). Otherwise, preparations for the future could be undermined by our inability to properly simulate or project new conditions outside our current modelling conditions.

Models are useful tools in hydrology and runoff has become a central feature in the modelling community to assess cumulative impacts (Futter et al., 2014; Lindström et al., 2010). Hydrological modelling has benefitted immensely from the use of long term runoff series from monitoring programs to gain insights on change in fundamental system behaviour (Karlsson et al., 2013) and to aid our understanding of watershed responses to both short and long term environmental changes (Wellen et al., 2014). While conceptualization of many of these hydrologic models is based on average natural rainfall-runoff processes derived from long term series, both simple and complex models still performed well in simulating long term dynamics at the watershed scale (Li et al., 2015). Growing complexity in hydrologic models has led to increasing equifinality (Beven, 2006) due to multi-dimensionality of compensatory parameter spaces. However, extensive explorations of parameter spaces in complex models have also helped to gain further insights on system behaviour beyond simple models.

Uncertainty in model predictions depends on the length of time series (Larssen et al., 2007). Despite strong arguments against the use of the term “validation” (Oreskes et al., 1994), it is still a norm in the hydrologic modelling community to calibrate to one condition and reevaluate the model on different conditions (Cao et al., 2006; Donigiang, 2002; Wilby, 2005). This has made split-sample testing a popular way of assessing the internal working process of a model in hydrologic study (Klemeš, 1986) before embarking on future projections. While modelling staged under this framework is usually based on average system conditions depicted by long term series, it may not fully reflect processes operating under very dry and wet hydroclimatic conditions. This can also be due in part to inherent structural uncertainties in models (Butts et al., 2004; Refsgaard et al., 2006) that can stem from conceptualization, scaling and connectivity of processes between the landscape mosaic patches of a watershed that the models are representing (Tetzlaff et al., 2008; Ren and Henderson-Seller, 2006). This is the case of Karlson et al. (2013) that showed increasingly large predictive uncertainty when their model was tested on over a century long record due to non-stationarity of the historical series. It is therefore inevitable that this level of uncertainty will be amplified when projected into the unknown future where, unlike at present, we have no data to confirm our findings (Refsgaard et al., 2014). However, no consensus has yet been reached regarding whether the uncertainty due to differences in hydrologic model structures and/or calibration strategies would be greater than the unresolved uncertainty inherent in climate models when projecting hydrologic conditions in boreal or temperate ecozones.

One way to constrain the uncertainty in hydroclimatic projections is to utilize historical wet and dry years as a proxy for the future conditions expected as climate changes. This is analogous to differential split-sample test previously used (Coron et al., 2012; Klemeš, 1986; Seibert, 2003; Refsgaard and Knudsen, 1996) but is less commonly used in hydrology (Refsgaard et al., 2014). Here we used hydrological and meteorological observations in dry and wet years in a long term monitored headwater catchment in northern Sweden. The objectives of this study were to: 1) utilize long term field observations in Svartberget to gain insights into hydroclimatic behaviour in dry and wet years as a proxy to future climate extremes and 2) quantify the uncertainty in our current predictive practices that is based on such long term series. Our expectation is that the uncertainty assessment conducted in this study will help to test whether our current predictive uncertainty regarding future extremes could be attributed to inherent uncertainties in climate models or is driven by differences in hydrologic model calibration strategies.

2 Data and method

2.1 Study site

This modeling exercise was carried out in Svartberget (64° 16'N, 19° 46' E), a 50 ha headwater boreal catchment within the Krycklan experimental research infrastructure in northern Sweden (Fig. 1) (Laudon et al., 2013). Modelling results presented here were based on the long-time series of precipitation, air temperature and runoff (1981-2012) from a weather and flow monitoring station at the outlet of Svartberget. Svartberget has two headwater streams, one of which drains a completely forest landscape while the other drains a headwater mire. The catchment has a long term mean annual temperature of about 1.8°C with minimum (January) and maximum (July) mean monthly temperatures of -9.5°C and 14.5°C. The catchment receives a mean annual precipitation of 610 ± 109 mm with more than 30% falling as snow (Laudon and Ottosson-Löfvenius, 2015). Snow cover usually lasts from November to May (Oni et al., 2013). The catchment has a long term mean annual runoff of 320 ± 97 mm with subsurface pathways dominating runoff delivery to streams. Spring melt represents the dominant runoff event in the catchment and lasts 4 to 6 weeks. Forest cover includes a century old Norway spruce (*Picea abies*) and Scot pine (*Pinus sylvestris*) with some deciduous birch species (*Betula spp*). *Sphagnum sp* dominates the mire landscape and riparian zones (Ledesma et al., 2016). Svartberget has gneissic bedrock overlain by compact till of about 30 m thickness to the bedrock. The catchment elevation ranges from 114-405 m above sea level and was delineated using DEM and LIDAR (Laudon et al., 2013).

2.2 Climate models

We used 15 different regional climate models (RCMs) from the ENSEMBLES project (Van der Linden and Mitchell, 2009, Table 1). All RCMs had a resolution of 25 km and were based on Special Report on Emission Scenario (SRES) A1B emission scenarios. The SRES A1B represents a balanced growth of economy and greenhouse gas emission in the future (IPCC, 2007). Precipitation and temperature values (2061-2090) were obtained by averaging the values of the RCM grid cell with center coordinates closest to the center of the catchment and of its eight neighboring grid cells. Due to systematic biases in RCM data and the spatial disparity between RCM grid cell and small catchment like Svartberget, post processing of RCM data is required Teutschbein and Seibert, 2012; Ehret et al., 2012; Muerth et al., 2013). The distribution mapping method (Ines and Hansen, 2006; Boe et al., 2007) was used for bias-correction of the 15 RCM-simulated precipitation and air temperature series on monthly basis using data from a weather station (1981-2010) located within the Svartberget catchment. This was achieved by adjusting the theoretical cumulative distribution function (CDF) of RCM-simulated control runs (1981-2010) to match the observed CDF. The same transformation was then applied to adjust the RCM-simulated scenario runs for the future (2061-2090). As some RCMs tend to simulate a large number of days with low precipitation (e.g. drizzle) instead of dry conditions, we applied a specific precipitation threshold to prevent considerable alteration of the distribution. RCM bias corrections presented here were fully described in Jungqvist et al. (2014) and Oni et al. (2014, 2015b).

2.3 Modelling and analysis

The Precipitation, Evapotranspiraton and Runoff simulator for Solute transport (PERSiST) is a semi-distributed bucket type rainfall-runoff model with a flexibility that allows modelers to specify the routing of water following the perceptual understanding of their landscapes (Futter et al., 2014). This feature makes PERSiST a useful tool to simulate streamflow from landscape mosaic patches at a watershed scale. The model operates on a daily time scale with inputs of precipitation and air temperature. The spatial interface requires an estimate of area, land cover proportion and reach length/width of the hydrologic response units. In the PERSiST application presented here, we used three buckets to represent the hydrology of Svartberget. These include snow, upper soil and lower soil buckets. In the snow routine bucket, the model utilized a simple degree day evapotranspiration and degree day melt factor (Futter et al., 2014). Although the maximum rate of evapotranspiration could be independent of wet and dry years as used in this study, the actual rate of evapotranspiration could be influenced by the amount of water in the soil and by an evapotranspiration (ET) adjustment parameter. The latter is an exponent for limiting evapotranspiration that adjusts the rate of evapotranspiration (depending on water depth in the bucket or how much is evapotranspired). The snow threshold partitions precipitation as either rain or snow. The model also simulates canopy interception for snowfall and rainfall to the uppermost bucket. In the modelling analysis presented here, we used three buckets to generate runoff processes in Svartberget. The quick flow bucket simulates surface or direct runoff in response to the inputs of rainfall or snowfall depending on antecedent soil moisture status. The runoff generation process was partitioned between the quick flow and lower soil buckets (upper and lower) following the square matrix described in Table 2.

We utilized Monte Carlo analysis to explore parameter spaces using a range of parameter values listed in Table 3. The evapotranspiration adjustment parameter sets the rate at which ET can occur when the soil is no longer able to generate runoff and this was set to 1 in the upper soil box. Maximum capacity is the field capacity of the soil that determines the maximum soil water content held. The time constant specifies the rate of water drainage from a bucket and requires a value of at least 1 in PERSiST. The relative area index determines the fraction of area covered by the bucket and is also set to 1 for our simulations. Infiltration parameters in each bucket determine the rate of water movement through the soil matrix. The model is based on series of first order differential equations that are solved sequentially following the bucket order in the square matrix. More detailed information about PERSiST parameterization and equations is provided in Futter et al. (2014).

The model was calibrated against streamflow to generate present day runoff conditions. Initial manual calibration was performed on the entire time series to minimize the difference between the simulated and observed runoff. The manual calibration also helped to identify a suite of parameters ranges to be used in the Monte Carlo analysis by varying each parameter value following steps listed in Futter et al. (2014). The Monte Carlo tool works in such a way that the Nash-Sutcliffe (NS) value for the overall period of simulation dropped close to zero instead of 1 similar to other works (Senatore et al., 2011; Mascaro et al., 2013). This helped to determine the ranges to use in the subsequent Monte Carlo analysis for the wet and dry year simulations. Starting from a random point, we sampled each parameter space 500 times before jumping to the next space (depending on whether the model performance was better or worse). We specified 100 iterations during the initialization of Monte Carlo tool so that 100 ensemble of credible parameter sets could be generated. This resulted in 50,000 (500 x 100) runs. In addition to Nash-Sutcliffe statistics, the Monte Carlo tool also takes note of other metrics during sampling. The Monte Carlo tool utilizes the Metropolis-Hasting algorithm and its mode of operation was described in Futter et al. (2014).

The best parameter sets (100 in this case) were selected based on highest NS statistics from untransformed/log transformed data. The parameter sets were also analyzed for other metrics such as variance of modeled/observed series (Var), absolute volume difference (AD), root mean square error (RMSE) and coefficient of determination (R^2). These top parameter sets derived from the Monte Carlo tool are referred to as behavioural parameters henceforth. The behavioural parameters were subjected to further analyses to determine hydrologic behaviour in dry and wet years. These include the cumulative distribution function (CDF) of behavioural parameters to determine the sensitive parameters and discriminant function analysis (DFA) to determine the dominant parameter(s) that separate the hydrology of wet from dry years. Wet years were defined as hydrologic years with runoff exceeding 430 mm/yr or 40% higher than average annual runoff (1995, 2002, 2005 and 2010). Dry years were defined as hydrologic years with runoff less than 150 mm/yr or less than 50% of average annual runoff (1987, 1992, 2000 and 2001). Hydrologic year was September 1 of a year to August 31 of the following calendar year. The bias corrected future climate series from the ensemble of climate models (Table 1) were used to drive PERSiST so as to project future hydrologic conditions under long term, as well as dry and wet year conditions.

3 Results

3.1 Long term climate and hydrology series

Preliminary analysis showed that the Svartberget hydroclimate was highly variable and thus helped partition the long term series into dry and wet years as shown in Supplementary Information 1 (SI 1). As a result, dry and wet year conditions differed in terms of climate and cumulative runoff patterns. The cumulative distribution of the dry/wet year series (Fig 2a) showed that dry year precipitation (462 ± 102 mm) was only 64% of precipitation observed in wet years (716 ± 56 mm). Similar patterns were observed in runoff dynamics (Fig. 2b) where total runoff in dry years (129 ± 35 mm) was 29% of total runoff observed in wet years (449 ± 19 mm). Runoff response was 63% of total precipitation in wet years and 28% of precipitation in the dry year regime (Table 4). Mean annual temperature was 2.4 ^{o}C in wet versus 1.8 ^{o}C in dry years.

When assessed on a seasonal scale, both precipitation and runoff were higher in almost all months in wet compared to dry year conditions (Fig. 3) but differed in terms of seasonal patterns. While runoff peaked in May in both wet and dry years reflecting spring snowmelt dynamics that characterize Svartberget, runoff magnitude differed. Peak precipitation events occurred in summer months with additional autumn peaks in wet year. However, there was a shift in precipitation patterns with lowest precipitation in February/March in dry years compared to April in wet years. Winter months were generally slightly warmer during wet years and summers slightly warmer in dry years (Fig 3c).

3.2 Future climate projections

There was less agreement between the observed series and uncorrected individual RCMs (SI 2a, b). However, bias correction helped to reduce the uncertainty on the historical time scale by providing a better match for the ensemble mean of the air temperature and precipitation with their corresponding observed series (SI 2c, d). The ensemble mean performed better in fitting observed air temperature than precipitation. There is also a possible increase in air temperature by 2.8-5^{o}C (median of 3.7^{o}C) and possible increase in precipitation by 2-27% (median of 17%). Although precipitation and temperature were projected to increase throughout the year, the temperature changes would be more pronounced during winter months irrespective of whether it was a dry or wet year (Fig. 3c). However, projected changes in precipitation followed similar patterns to historical wet years with more precipitation expected between late winter months through spring (Fig. 3a). Result also showed that the winter period with temperature below 0^{o}C could be shortened as climate warms in the future (SI 2).

3.3 Model calibrations and performance statistics

Model behavioural performance followed similar patterns when metrics such as R^2, NS and log NS were used (SI 3a-c) and metrics could be used interchangeably to measure model performances. The model performed better when calibrated to wet and dry conditions (compared to long term) using NS metrics (SI 3b, c). Although no major improvements to model efficiency above NS of 0.79 and 0.81 were obtained in dry and wet years, respectively, we obtained a wider range of model performances in wet relative to dry year. The patterns of other performance metrics were different as we observed the highest RMSE in dry years and lowest RMSE in wet year condition (SI 3d). There was minimum AD range in the long term record and maximum range in dry years (SI 3e). Model performances based on the Var metric also showed the largest variability in dry years compared to the long term record and least Var in the wet year (SI 3f).

3.4 Runoff simulations and behavioural prediction range

Using the best performing parameter sets based on the NS statistic as an example, the model performed well in simulating interannual runoff patterns but underestimated the peaks (SI 4). When resolved to their respective dry and wet year components, the model performed better in simulating runoff conditions in wet years despite its larger data spread and higher spring peaks than the dry year regime (SI 5). When parameterization for dry years was used for runoff prediction in wet years, runoff was underestimated by 35% due to significant uncertainty that stemmed from the growing season months (Fig. 4). Modelling analysis also showed that no single metric can be an effective measure of model performance under dry and wet year conditions (Fig 5a- c). However, utilizing a behavioural mean of these different performance metrics (Fig. 5d-f) appeared to be a more effective way of calibrating to extremely dry and wet hydroclimatic conditions. While the behavioural mean performed better in simulating runoff dynamics in winter through spring in the long term record and significantly reduced the uncertainty in dry and wet years, larger uncertainty existed in summer through autumn months in dry and wet years compared to the long term record.

3.5 Parameter uncertainty assessments

While we observed a wide prediction range from behavioural parameter sets (Fig. 5), we have limited information on the underlining processes. Therefore, we subjected the behavioural parameter sets to further analysis to identify sensitive parameters and plausible patterns of hydrologic processes that differentiate dry and wet years (Fig. 6). The cumulative distribution function (CDF) of behavioural parameter sets showed that both rain and flow multipliers were sensitive parameters in dry years. The rain multiplier was less sensitive in wet years unlike the flow multiplier. Long term simulations showed no sensitivity to the rain multiplier but were sensitive to the flow multiplier. We observed similar patterns of response to the flow multiplier in all three hydrologic regimes (Fig. 6b).

Result also pointed to the sensitivity of interception in wet years but all the three hydrologic regimes showed similar patterns for the time constant (water residence time) in lower soil.

We subjected the pool of behavioural parameters in dry and wet year regimes to discriminant function analysis (DFA) to identify the key parameters that separate the extreme hydroclimatic conditions (Fig. 7). Results showed that both dry and wet years separated well in canonical space. However, the separation was driven mainly on quantitative parameters related to precipitation, interception and evapotranspiration on canonical axis 1 (Rmult, Int and DDE). The parameters separated to a lesser extent on processes related to snow parameters on canonical axis 2 (Smult, SM and DDM).

3.6 Quantification of uncertainty in hydrologic projections

We compared the effects of different performance metrics in wet and dry year regimes to constrain uncertainty in runoff projections under future hydroclimatic extremes in Svartberget catchment (SI 6). Results showed that differences in model representation of present day conditions might be minimal (compared to the observed) but a wide range of runoff regimes were projected in the future. We also observed small difference in the range of runoff projections (derived from minimum and maximum of behavioural parameter sets) using different model performance metrics. Uncertainties inherent in climate models (as opposed to differences in calibration or performance metrics) appeared to drive the overall uncertainty in runoff projections under dry and wet hydroclimatic conditions**.** Wet year is the closest to plausible projections of future condition expected in the boreal ecozone. However, model results suggested that the uncertainty in present day long term simulations is mostly driven by dry years. We compared the runoff predictions using dry year parameterization to parameterization based on wet years to quantify our current predictive uncertainty. Results showed that future runoff could be under predicted by up to 40% (relative to wet year ensemble mean) if the projections are based on dry year parameterization alone (Fig. 8). Both parameterizations projected a shift in spring melt from May to April in the future. However, ensemble projections showed that summer months could be a lot wetter (based on wet year parameterization compared to dry year) and wet year spring peak could be up to 43% more compared to projections based on the wet year ensemble mean.

4 Discussion

4.1 Insights from long term hydroclimatic series

Several studies have evaluated the impact of climate change on surface water resources (Berghuijs et al., 2014; Chou et al., 2013; Dore, 2005 among the others) but most of these were based on long term series that depict average system behaviour. However, present day hydroclimatic extremes, such as those derived from historical wet and dry years, can be used as simple proxies to gain insights that will aid our understanding of future hydroclimatic conditions. Using this approach we found that standard calibrations can result in underestimation of runoff by up to 35% due to high variability of hydroclimate series in northern boreal catchments. Several explanations can be offered for the high variability in the long term hydroclimate series at the study site. First, snowmelt hydrology is important in understanding the boreal water balances due to their location in the northern hemisphere (Euskirchen et al., 2007; Dore, 2005; Tetzlaff et al., 2011, 2013). As a result, northern headwater catchments tend to show high variability (Brown and Robinson, 2011; Burn, 2008).

We observed annual runoff yield to be 63% of total precipitation in the wet years compared to 28% of total precipitation in dry year. More runoff yield in the wet year regime could be seen as a result of near field capacity of the soils throughout the year, leading to greater propensity for runoff generation because hydrological conductivity increases towards soil surface in the catchment (Nyberg et al., 2001). This can also imply more winter snow accumulation during the long winter period, resulting in higher spring melt that drives the overall water fluxes (Laudon et al., 2004). Less runoff yield in dry years could be attributed to higher soil moisture deficit and relatively more important evapotranspiration rates (Dai, 2013).

We also observed differences in dry/wet year peak summer precipitation and a shift in the lowest precipitation in late winter/early spring. Despite the differences in precipitation, we observed similar patterns of runoff responses that only differ in terms of magnitude. This suggested that there was more effective rainfall (net available water) available to infiltrate, continuously recharge groundwater systems and generate runoff from upstream sources in wet year. Slightly warmer temperatures in summer months could drive more of growing season evapotranspiration in dry year. Small differences in temperature regime between wet and dry year, unlike precipitation, also explained why larger uncertainty and biases still exist during post-processing of precipitation series in using any scenario-based GCMs as observed in SI 2.

4.2 Multi-criteria calibration of hydrological models

There has been considerable discussion about the calibrating procedure in the hydrological modelling community (Andreassian et al., 2012; Boij and Krol, 2010; Efstratiadis and Koutyiannis, 2010; Oreskes et al., 1994; Price et al., 2012). One of the key reasons for this is the difference in goodness-of-fit measures utilized in each model (Krause et al., 2005; Pushpathala et al., 2012). The most common strategy is to calibrate hydrologic models using the Nash-Sutcliffe (NS) statistic (Nash and Sutcliffe, 1970). However, many modelers believe that the NS-based method alone tends to underestimate variance in modelled time series as this metric could be biased toward high or low flow periods

(Futter et al., 2014; Jain and Sudheer, 2008; Pushpalatha et al., 2012). This is promoting our use of multi-criteria statistics in model calibrations to constrain predictive uncertainty in hydrologic projections to extreme dry and wet hydroclimatic conditions. Therefore, multi-criteria calibration objectives that assessed model performances using different goodness-of-fit metrics could aid our understanding of hydrologic behaviour in boreal catchments. Our observation of differences in model performances in terms of NS and other metrics presented here is expected as a three box model proposed by Seibert and McDonnell (2002) similarly showed good fit for NS but poor fit using other metrics. However, lower model performance (based on NS) for the long term record is explainable as most hydrologic models are based on average system behaviour represented by long term rainfall-runoff processes (Futter et al., 2014; Oni et al., 2014b; Wellen et al., 2014).

The lower range of model performances in calibrating to the observed runoff in dry years is an indication of variable runoff generation processes associated with this wetness regime. Dry years cause drought-like conditions (Dai, 2011; Mishra and Singh, 2010) as a result of less water availability that reduces hydrologic connectivity within the catchment. However, the model performed better when applied to wet and dry years individually compared to the long term record based on NS statistics. This suggested that the mechanisms driving hydrologic processes in dry and wet years might be similar but their relative magnitude differs from long term average conditions (Grayson et al., 1997). Better performance under dry and wet conditions (compared to average long term) can also be attributed to the bias of NS and log NS towards high flows and baseflow, respectively (Futter et al., 2014; Jain and Sudheer, 2008; Pushpalatha et al., 2012).

However, NS statistics alone are not enough to assess model performances in climate-sensitive boreal headwater streams such as Svartberget. Other metrics such as the RMSE showed that dry years could be a major driver of the uncertainty we observed in simulating the long term record. A possible explanation could be that the soil moisture deficit is larger in dry year, leading to soil matrix or vertical flow (Grayson et al., 1997) that can only generate runoff after filling soil pore spaces (McDonnell, 1990). For example, soil pore spaces are usually not close to saturation under dry condition due to 1) intermittent precipitation events throughout the year and 2) several patchy source areas of high water convergence that are characterized by local landscape terrain or soil properties (Fang and Pomeroy, 2008; Jencso et al., 2009). Also higher rates of evapotranspiration coupled with low precipitation can contribute to more spatially decoupled antecedent soil moisture conditions and thus lower runoff in dry years (Dai, 2013; Vicente-Serrano et al., 2010). Therefore, no single model performance metric can be effective in simulating the hydrology of dry and wet year conditions, as our results showed that the mean of behavioural metrics outperformed any individual metric in dry and wet years under present day conditions.

4.3 Parameter sensitivity in dry and wet year regimes

The robust uncertainty assessment conducted here showed that extensive exploration of model parameter spaces suggests how hydrologic behaviour differs between wet and dry year regimes. A possible explanation for the non-sensitivity of the rain multiplier in wet years could be attributed to 1) a more consistent or stable precipitation feeding the system throughout the year compared to intermittent precipitation in dry years (Fang and Pomeroy, 2008; McNamara et al., 2005) or 2) the effect of rain water collector missing proportionally more rain in dry than wet years. This can explain the smaller spring peak that characterizes the dry year regime or its non-sensitivity to interception unlike its role in wet year regimes.

We observed that sensitivity of the lower soil time constant followed similar patterns in dry and wet years unlike the upper soil box. Therefore, we could expect faster flow and higher runoff ratio in the wet years due to rapid response to precipitation events and more macropore flow (Peralta-Tapia et al., 2015). This can lead to steady runoff generation due to 1) near saturation of soils and 2) greater connectivity between stream channels and upland areas (Bracken et al., 2013; Ocampo et al., 2006) that become disconnected in dry years. The patterns of the flow multiplier parameter showed that both dry and wet year conditions followed similar runoff generation processes. These suggested that the main physical mechanisms to explain parameter sensitivity and hydroclimatic behaviour to dry/wet conditions were related to differences in their precipitation patterns rather than landscape-driven hydrologic processes.

4.4 Drivers of hydrologic behaviour in dry and wet year regimes

Even though equifinality limits the use of CDFs alone in identifying all sensitive parameters, DFA of behavioural parameters gave further holistic insights into plausible differences in wet/dry hydrologic behaviour when projected on canonical space. This suggested that hydrological model parameterizations calibrated to high flow associated with wet years differ from parameterizations for long term or dry conditions. Therefore, parameter separation primarily on quantitative parameters (Rmult, Int and DDE) related to rainfall and evapotranspiration on canonical axis 1 suggested that climate is still a first order control of dry and wet year hydroclimatic regimes in the boreal forest. This is consistent with Wellen et al. (2014), who showed that extreme conditions could be triggered in a watershed when precipitation reaches a threshold that can initiate saturation overland flow. This is because soils are always near saturation capacity under prolonged wet conditions (Grayson et al., 1997). This can explain the increase in hydrologic model uncertainty in capturing the peak runoff events in wet years unless parameter ranges that combined different performance metrics are considered. Unfortunately, we might face a new challenge of increased precipitation ranges in the future as climate changes (Chou et al., 2013; Dore, 2005). The separations of wet and dry years on snow process-related parameters (Smult, SM and DDM) to a lesser extent on canonical axis 2 suggested that indirect landscape influences on snow processes could be important but are a second order control on runoff response to dry and wet conditions. This agrees with Jencso et al. (2009), who showed that landscape mosaic structures with their unique source contribution areas control the overall watershed response.

4.5 Implications for future climate projections

All 15 RCMs considered in this study projected a range of plausible futures in the Swedish boreal forest. Irrespective of the model performance metrics, results suggested that the future could be substantially wetter and could make drought conditions less severe in boreal ecozones. This could explain the large uncertainty in projecting runoff under wet conditions. For example, dry year and long term parameterizations were similar and runoff was under-predicted by 35% under the present day condition when parameterization in dry years was used for wet years. This was due to large predictive uncertainty in runoff dynamics (Fig. 4) that resulted from high evapotranspiration rates during the snow free growing seasons in dry year. This suggests that wet year calibration could give more credible projections of the future in the boreal ecozone as the distribution of precipitation in wet years is closer to the precipitation pattern expected in the future. While our modelling results suggested negligible differences in runoff projections based on either dry year or long term parameterization, wetter conditions could become a more dominant feature in the boreal ecozone.

These have implications for future climate change as both dry and wet year parametrization showed a consistent shift in spring melt patterns from May to April (Fig. 8). This temporal advance in spring melt patterns could result from altered distribution of snowfall and rainfall patterns in the winter (Berghuijs et al., 2014; Dore, 2005), and may likely have effects on soil frost in the upper layer (Jungkvist et al., 2014) or change in evapotranspiration rates (Jung et al., 2010; Vicente-Serrano et al., 2010). Therefore, intensification of hydroclimatic regimes as climate changes in the future (Kunkel et al., 2013) could drive water quality issues to a new level in the boreal forest due to changes in the flux of organic carbon and aquatic pollutants. Furthermore, precipitation has been shown to have much larger biogeochemical implications for the boreal carbon balance than previously anticipated (Öquist et al., 2014).

The large spread of mean annual runoff projected by each RCM in wet years is an indication of less agreement between RCMs when predicting future conditions. This suggested that inherent uncertainty in climate models, rather than differences in model calibrations, drive the overall uncertainty in runoff projections. However, hydrologic model calibration for climate impact studies should be based on years that closely approximate anticipated conditions to better constrain uncertainty in projecting extremely dry and wet conditions in boreal and temperate regions.

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Table 1: List of RCMs from EU ENSEMBLES project used in this study and their respective driving GCM.

No.	Institute	RCM	Driving GCM
1	**C4I**	RCA3	HadCM3Q16
2	**CNRM**	Aladin	ARPEGE
3	**DMI**	HIRHAM5	ARPEGE
4	**DMI**	HIRHAM5	BCM
5	**DMI**	HIRHAM5	ECHAM5
6	**ETHZ**	CLM	HadCM3Q0
7	**HC**	HadRM3Q0	HadCM3Q0
8	**HC**	HadRM3Q16	HadCM3Q16
9	**HC**	HadRM3Q3	HadCM3Q3
10	**ICTP**	RegCM	ECHAM5
11	**KNMI**	RACMO	ECHAM5
12	**MPI**	REMO	ECHAM5
13	**SMHI**	RCA	BCM
14	**SMHI**	RCA	ECHAM5
15	**SMHI**	RCA	HadCM3Q3

Table 2: Square matrix used to partition runoff generation between buckets in PERSiST application presented here. For example, we conceptualized that 40% of the precipitation inputs are retained in the upper box, 60% are transferred to the lower box and 0% are transferred to the groundwater (row 1)

	Upper box	Lower box	Groundwater
Upper box	0.4	0.6	0
Lower box	0	0.5	0.5
Groundwater	0	0	1

Table 3: Parameter notations, descriptions and ranges used in the Chain Monte Carlo analyses in this study

	Notation	Parameter description	Min	Max	Units
SNOW	SMt	Snowmelt temperature	-3	5	^{o}C
	ISD	Initial snow depth	40	120	mm SWE
	DDM	Degree day melt factor	1	4	mm ^{o}C day^{-1}
	DDE	Degree day evapotranspiration	0.05	0.3	mm ^{o}C day^{-1}
	GDT	Growing degree threshold	-3	3	^{o}C
	Smult	Snow multiplier	0.5	1.5	-
	RM	Rain multiplier	0.5	1.5	-
	CI	Canopy interception	0	4	mm day^{-1}
UPPER BOX	IWD_1	Initial water depth	40	100	mm
	RWD_1	Retain water depth	100	250	mm
	Infilt_1	Infiltration	1	15	mm day^{-1}
	DRF	Drought runoff fraction	0	0.5	-
	REI	Relative evapotranspiration index	1	1	-
	EA_1	Evapotranspiration adjustment	1	10	-
LOWER BOX	IWD_2	Initial water depth	80	250	mm
	Infil_2	Infiltration	1	15	mm day^{-1}
	RWD_2	Retain water depth	200	200	mm
	TC_2	Time constant	2	50	days
	EA_2	Evapotranspiration adjustment	0	0	-
	InunT_2	Inundation threshold	80	150	mm
GROUNDWATER	IWD_3	Initial water depth	80	250	mm
	Infilt_3	Infiltration	0.1	10	mm day^{-1}
	EA_3	Evapotranspiration adjustment	0	0	-
	RWD_3	Retain water depth	250	250	mm
	TC_3	Time constant	2	50	days
REACH	a	Flow multiplier	0.004	0.762	-
	b	Streamflow exponent	0.01	0.98	-
	ST	Snow threshold temperature	-2	3	^{o}C

Table 4: Quantification of runoff and precipitation dynamics in wet and dry year using the observed series and simulated series from PERSiST.

	Observed series (%)	Simulated series (%)
Precipitation proportion (dry:wet year)	64	
Runoff proportion (dry:wet year)	29	29
Runoff response to precipitation events		
Dry year	28	30
Wet year	63	66

Figure 1: Svartberget, a long term monitored headwater catchment in the northern boreal ecozone of Sweden. The catchment (50ha) drains terrestrial area consisting of forest (82%) and upland mire (18%). Streamflow measurements were taken at the downstream confluence point .

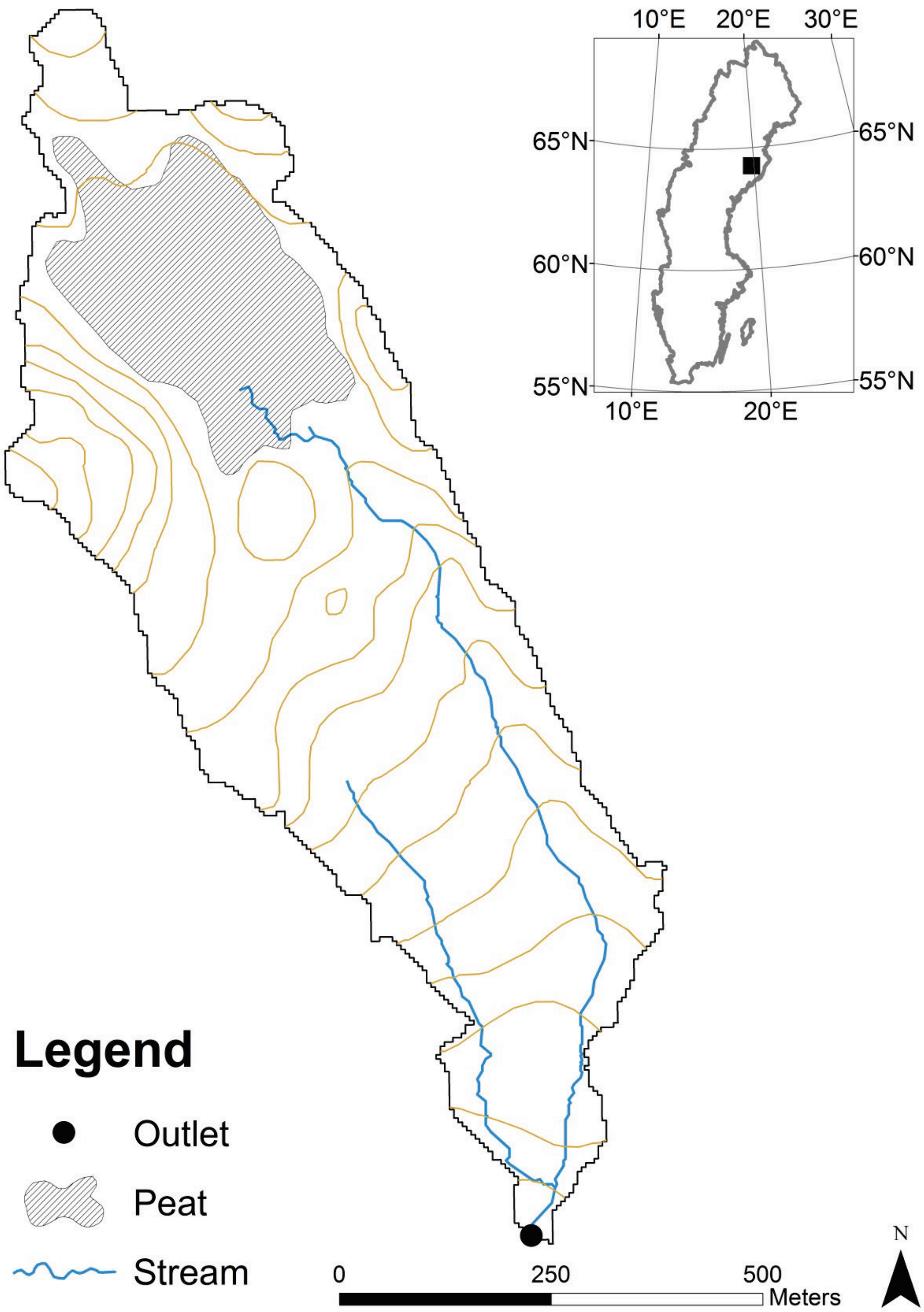

Figure 2: Cumulative plots of (a) precipitation and (b) runoff in dry (1995, 2002, 2005 and 2010) and wet (1987, 1992, 2000 and 2001) hydrologic years. Hydrologic year is September 1 (day 1) to August 31 of the following year (day 365). The cumulative plots shown here represent average for all the dry and wet years noted above.

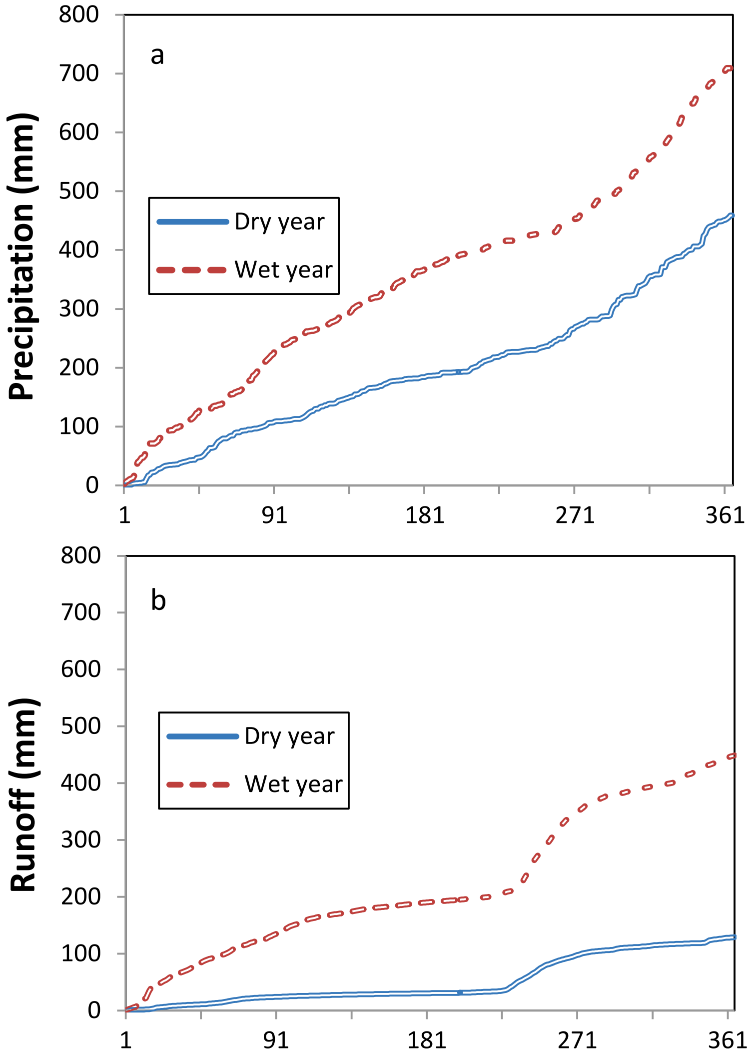

Figure 3: Seasonal patterns of (a) present day precipitation in dry and wet years versus ensemble mean (bias-corrected) of future precipitation projections, (b) present day runoff dynamics in dry and wet year and (c) present day temperature in dry and wet years relative to ensemble mean (bias corrected) of future temperature projections. Note that the dry and wet years in these plots represent average of all the individual dry and wet years respectively.

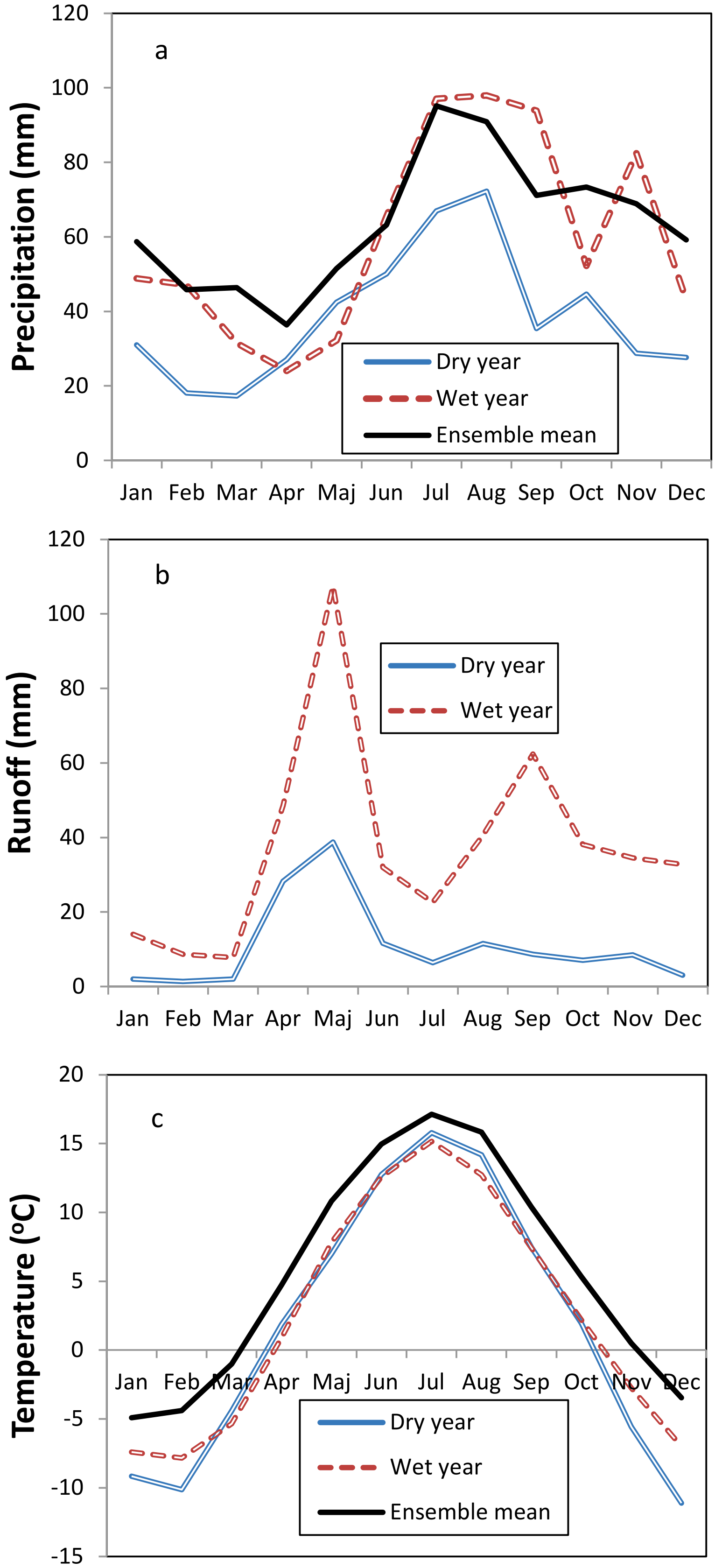

Figure 4: Quantification of predictive uncertainty in runoff simulations when best parameter set (based on NS) calibrated for dry year was used for wet year observed series.

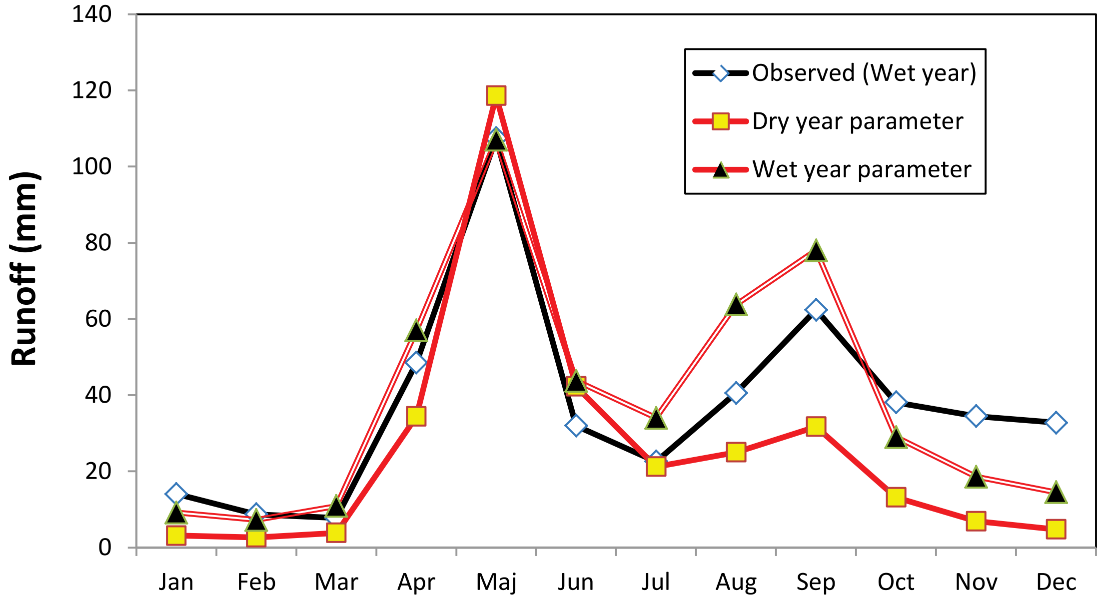

Figure 5: Summary plots showing prediction range of seasonal runoff dynamics of behavioural parameter sets using different performance metrics in a) dry year, b) wet year and c) long term. (d) to (f) show the corresponding model performances using behavioural mean of the metrics in (a) to (c).

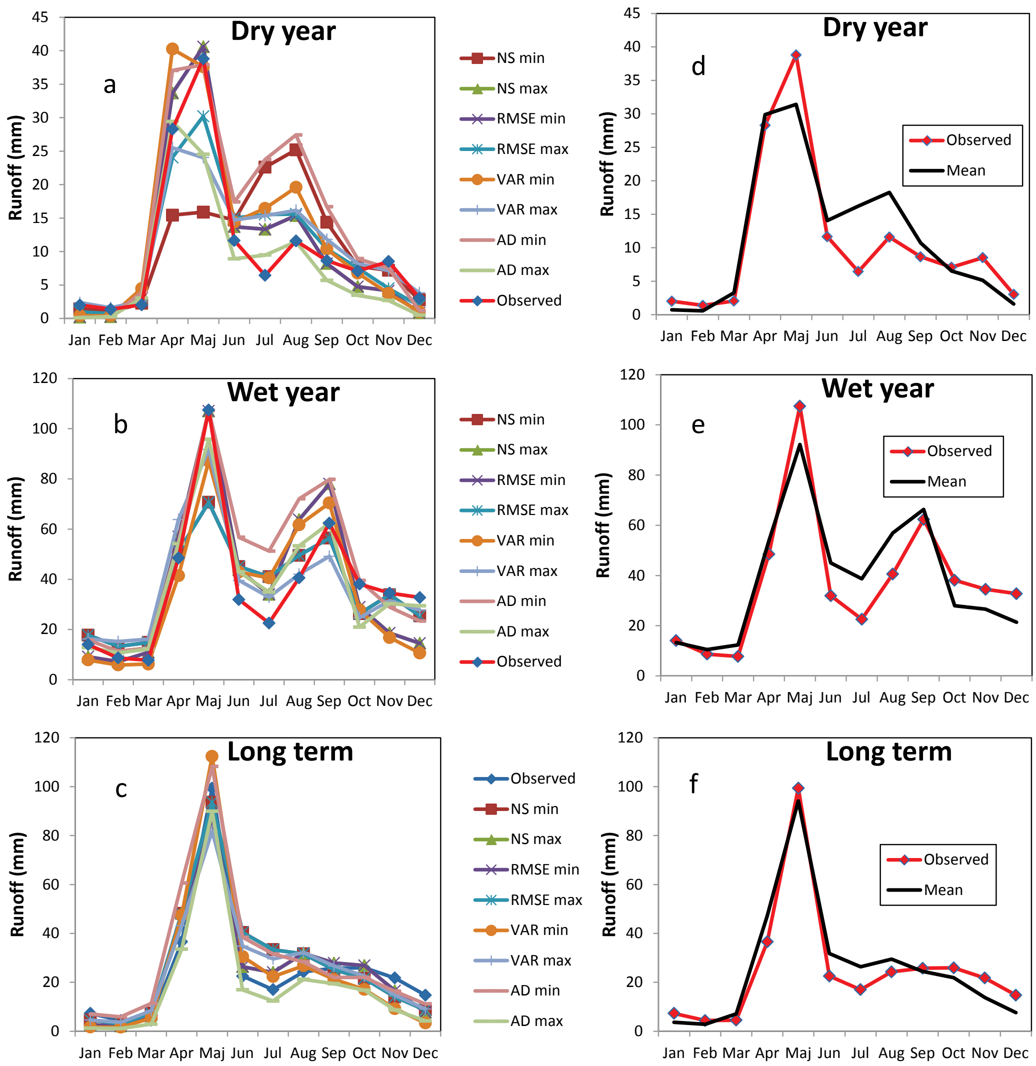

Figure 6: Cumulative distribution function (CDF) of behavioural parameters (top 100 iterations from the MCMC) in wet and dry years versus long term record. (a) is the rain multiplier, b) is the flow multiplier, c) is the interception and d) is the lower soil time constant in the lower soil box. A rectangular distribution (straight line plot) defines parameter behaviours that were not sensitive (not left- or right-skewed).

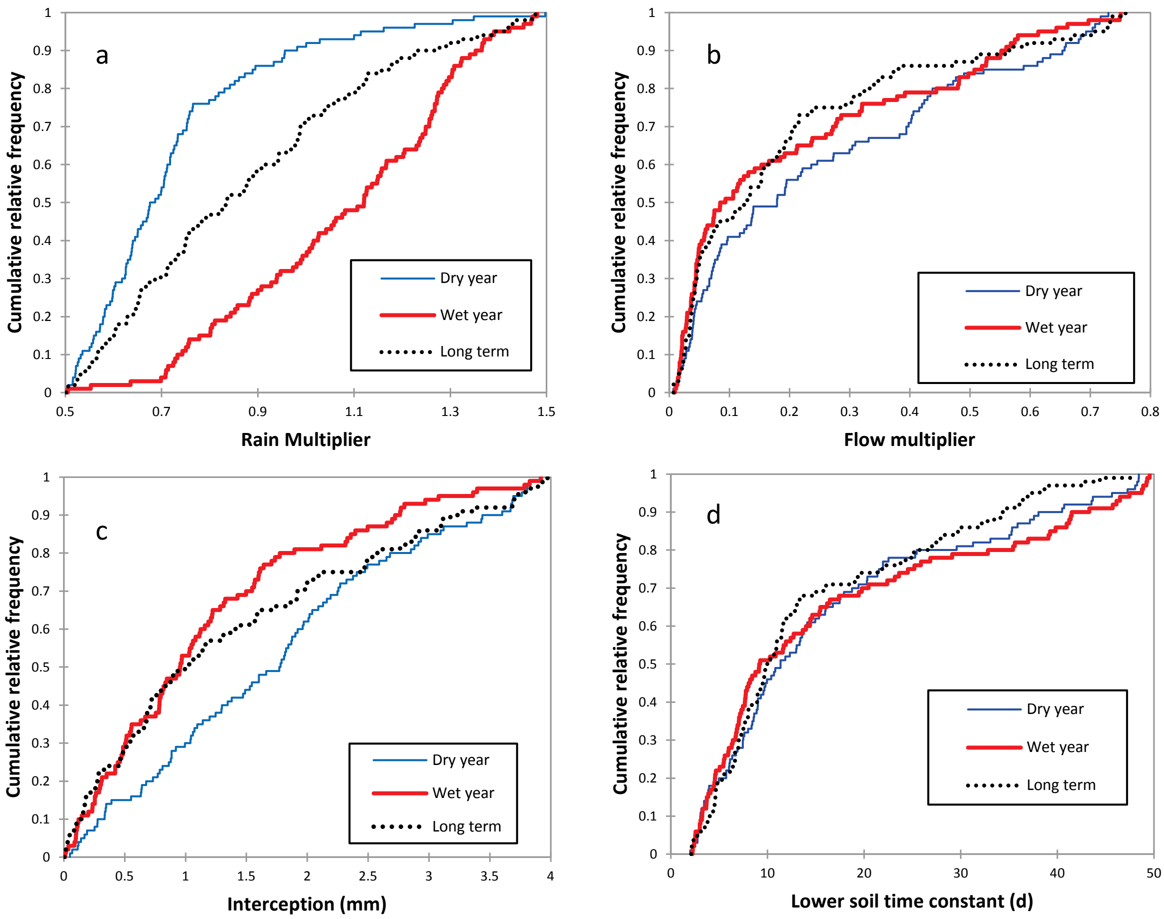

Figure 7: Separation of the behavioural parameter sets (top 100 iterations from MCMC) in the dry and wet year hydrologic regimes using Discriminant Function Analysis (DFA). Wet and dry year hydrology separated mainly on parameters related to evapotranspiration (DDE), interception (Int) and rain multiplier (Rmult) on canonical 1. Parameters were separated on snow multiplier (Smult), snowmelt (SM) and degree day melt factor (DDM) on canonical 2. The circles represent normal 50% contours. Parameters are defined in Table 3.

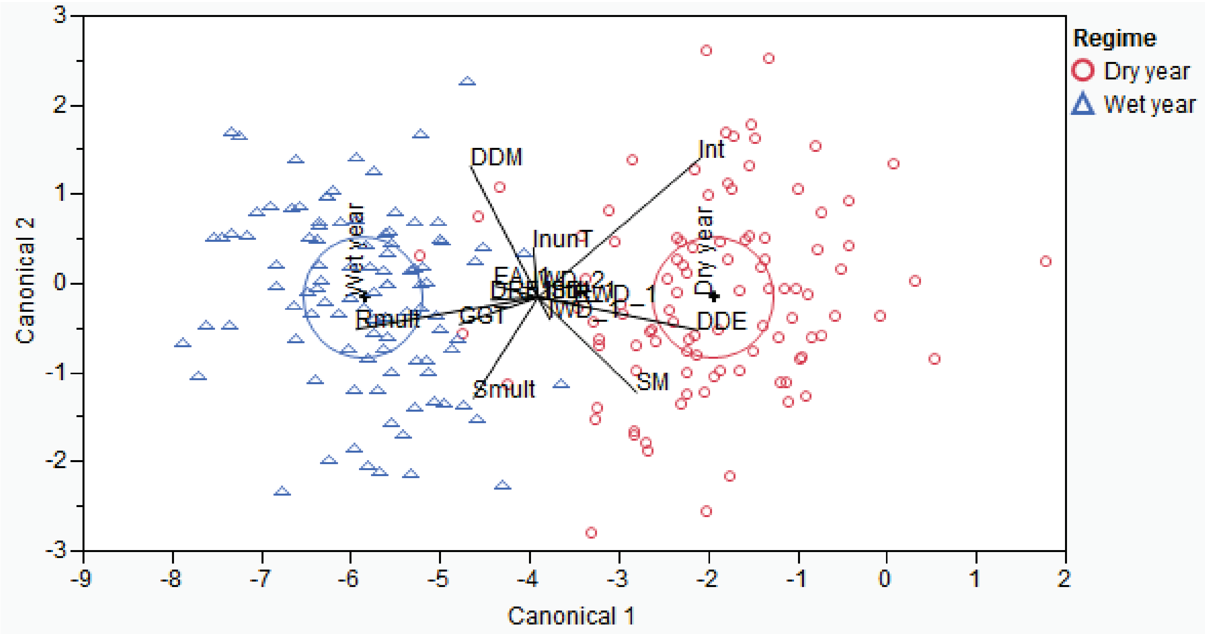

Figure 8: Example of range of runoff projection using wet year parameterization that closely depicts the future versus projected range based on dry year parameterization. The projected range was simulated to constrain uncertainty in extreme wet and dry conditions in the future using the behavioural parameter sets (top 100 iterations from MCMC) for each of the 15 RCM scenarios (100 parameters by 15 RCMs = 1500 runs each for dry and wet year).Ensemble mean represents the mean of the 1500 realizations while long term depicts mean of the long term series.